Changing Tracks:
Human Capital Investment after Loss of Ability*

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Abstract

We provide the first evidence on how workers invest in human capital after losing ability. Using quasi-random work accidents in Danish administrative data, we find that workers enroll in bachelor's programs after physical injuries. Exploiting differences in eligibility driven by prior vocational training, we find that higher education moves injured workers from disability benefits to full-time employment. Reskilled workers earn 25% more than before their injuries and avoid ending up on antidepressants. Reskilling subsidies for injured workers pay for themselves four times over, and current rates of reskilling are substantially below the social optimum, especially for middle-aged workers.

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1 Introduction

The transition of workers from physical to cognitive occupations is a core goal of modern reskilling programs. By providing the human capital necessary for such transitions, the programs promise to alleviate earnings shocks from automation, globalization, and physical injuries.[1] Human capital investment may also help lift exposed workers out of disability insurance programs, which consume a substantial and growing proportion of government budgets in advanced countries (Autor and Duggan (2006); OECD (2023c)). More broadly, work accidents are costly to workers, firms, and the government, yet evidence documenting the impact of reskilling programs on disabled workers is limited.

To help fill this gap, we study reskilling and occupational transitions in the context of work accidents, a severe shock to the ability of workers. We contribute to the literature by answering three fundamental questions: Do workers invest in human capital after losing physical ability? Do human capital programs help workers switch from physical to cognitive occupations? What are the returns on these investments for workers and society?

To answer these questions, we link micro data on the health shocks, human capital investments, and employment outcomes of workers in Denmark from 1995 to 2017. Our analysis proceeds in three parts.

First, we study how workers invest in human capital after losing physical ability. For this analysis, we document that work accidents occur quasi-randomly within occupations, as affected and non-affected workers have similar health and earnings before accidents. Work accidents cause permanent damage to the livelihoods of workers whose labor earnings suffer a persistent 40% loss while antidepressant prescriptions increase by 10 percentage points. We establish four findings about how workers invest in human capital after losing ability. First, most injured workers do not invest in human capital.

[1] The World Economic Forum has called for a "Reskilling Revolution" to alleviate the automation of manual jobs (World Economic Forum (2019)). Trade Adjustment Assistance provides reskilling vouchers for workers displaced by import competition in the United States (U.S. Department of Labor (2022)). Workers' Compensation includes vouchers for injured workers to reskill (Department of Industrial Relations (2022)).

Ten years after the work accidents, about 13% of workers have enrolled in a degree at any level, and participation in non-degree courses is negligible. Second, workers who invest in human capital overwhelmingly enroll in four-year bachelor's programs, suggesting that a substantial human capital investment is needed to change tracks. Third, workers select degrees that build on their work experiences and provide pathways to cognitive occupations with lower physical demands. Finally, investment decreases steeply with age; workers older than 50 do not invest in education after work accidents. By contrast, about half of the workers aged 20 to 25 pursue higher education after injuries.

In the second part of the paper, we study how reskilling through higher education affects the labor market outcomes of injured workers. To identify causal effects, we exploit that only a subset of vocational degrees grants direct entry into post-secondary programs in Denmark. For example, prior vocational training in carpentry provides direct admission into the bachelor's program in Construction Architecture. By contrast, landscape gardening (an otherwise similar vocational degree to carpentry) does not offer entry to any post-secondary program, so a worker would have to complete high school to become eligible for higher education.

We conduct a host of checks for whether workers with different access to higher education are otherwise comparable. First, we ensure that the workers are similar on observables before the accidents and verify that they experience comparable injuries.[2] Second, we document that the workers have similar earnings profiles and human capital investments if not hit by a work accident. The workers even fare similarly after temporary work injuries that do not induce workers to reskill. Third, we show that the oldest workers, who do not invest in human capital regardless of eligibility, perform similarly in the labor market after work accidents.

Comparing workers with different access to higher education, we estimate sizable earnings gains from reskilling for injured workers. Reskilled workers do not claim disability

[2]We validate that the workers have similar grades from primary school, total years of schooling, parental education and wealth, savings behaviors, residence and family situations, and commuting distances to higher education before the injuries. These balance checks suggest workers with access to higher education are not more able nor anticipate the need to reskill.

benefits and instead transition into cognitive occupations, earning 25% more than before their injuries. Without access to higher education, by contrast, these workers end up entirely on disability benefits and often resort to taking antidepressants. Combining the effects on earnings, taxes, and transfers in a cost-benefit framework, we calculate a 680% social return on higher education for injured workers. These remarkable social returns reflect that higher education moves injured workers from disability benefits (a liability to the government budget) to taxable high-income employment (an asset to the budget). In total, the government reaps about 60% of the net income from reskilling despite covering tuition and generous benefits.

In the final part of the paper, we evaluate the counterfactual effects of reskilling more injured workers. To do so, we estimate marginal treatment effects (MTE) of reskilling by interacting our "access to higher education" instrument with workers' age and commuting distances to higher education facilities. We identify the private, public, and social returns to reskilling for workers at the margin of participation at different levels of program expansion. We incorporate general equilibrium effects by embedding the treatment effects into a calibrated model of the labor market.

We find that injured workers reskill based on their idiosyncratic returns, such that expanding the program implies rolling it out to workers with lower returns to reskilling. We use the marginal treatment effects to determine the optimal rates of reskilling for injured workers. Averaging across age cohorts, we find a socially optimal rate of 33%, more than twice the current level. The current rates are especially sub-optimal for middle-aged workers between the ages of 40 and 50. In particular, only 6% of middle-aged workers reskill after injuries, yet reskilling subsidies covering tuition and benefits pay for themselves for 34% of these workers. From the viewpoint of middle-aged workers, a reskilling share of around 39% would maximize their present-discounted lifetime income. The fact that so few of the workers reskill points to substantial barriers to investing in human capital. In particular, the marginal middle-aged worker currently leaves $75,000 on the table by not reskilling. By contrast, the current reskilling rates among the youngest and oldest workers are close to optimal, socially and privately. We provide quantitative evidence on the roles of access to education, commuting costs, and financial constraints in preventing workers from reskilling.

1.1 Related Literature

Our main contribution is to provide evidence on how disabled workers invest in human capital and how these investments ease the transition into cognitive occupations. Our results relate to several strands of literature.

First, work accidents are pervasive in manual occupations and cause severe harm to workers and governments. Compared to mass layoffs, a shock to workers frequently studied in the labor literature (Jacobson, LaLonde, and Sullivan (1993); Sullivan and Von Wachter (2009)), work accidents are both more prevalent and cause more persistent earnings losses.[3] In the United States, work injuries are a leading cause of disability insurance claims, and their total costs amount to 1.3% of the Gross Domestic Product (Reville and Schoeni (2004); Leigh (2011)). More generally, health shocks have severe consequences for workers' employment and well-being (Dobkin et al. (2018); Meyer and Mok (2019)) and are an important determinant of inequality in lifetime earnings (Hosseini, Kopecky, and Zhao (2021)).

Our findings show how higher education may help injured workers return to work and avoid disability insurance. Disability insurance programs consume a substantial fraction of government budgets, yet we have limited evidence on policies that help workers reattach to the labor market (Autor and Duggan (2010)). Existing studies of disability insurance have mostly focused on benefit generosity in discouraging workers from returning to work (Maestas, Mullen, and Strand (2013); Kostøl and Mogstad (2014); Low and Pistaferri (2015); Autor et al. (2016)). More recently, Aizawa, Mommaerts, and Rennane (2023) study the role of wage subsidies in retaining injured workers at their original employers. We complement this work on retention by studying human capital

[3] See Section 3.1, and Figures A.1 and A.2.

policies to help workers change tracks more fundamentally in the labor market. In line with our results, Markussen and Røed (2014) provide evidence for using wage subsidies for milder injuries and regular education for more severe disabilities, especially among younger workers. Our study highlights the complex interactions between educational policy and social insurance.

Second, our findings inform policies to help displaced workers (Jacobson, LaLonde, and Sullivan (2011)). Reskilling programs are often motivated by structural changes, such as automation or globalization, forcing workers to switch out of manual occupations (Hyman (2018)).[4] Interestingly, work accidents, automation, and globalization share implications for workers as they all lower the earning potential of manual work. Our empirical evidence spotlights the importance of four-year bachelor's degrees in helping workers switch from manual to cognitive occupations. While there is a wealth of research on the effects of attending college before entry into the labor market (Altonji, Arcidiacono, and Maurel (2016)), we know little about the role of higher education in reskilling older workers. Similarly, we have extensive literature on the impact of active labor market programs on unemployed workers, but existing studies focus on shorter-term training interventions.[5] We provide the first instrumental variable (IV) estimates of the returns to higher education for workers hit by a career shock.[6] Our findings for experienced mid-career workers complement recent evidence on sectoral training programs in placing marginalized young workers in high-wage jobs (Katz et al. (2022)). By reorienting workers toward in-demand occupations, reskilling policies may have smaller displacement effects in the labor market than pure job-search assistance (Crépon et al. (2013)). In particular, we show that the optimal rates of reskilling for injured workers are robust to general

[4]In the United States, the Manpower Development and Training Act (MDTA) was enacted to alleviate industrial automation. Trade Adjustment Assistance (TAA) provides reskilling vouchers for workers displaced by import competition.

[5]Card, Kluve, and Weber (2018) survey more than 200 studies of active labor market programs but identify no study focused on post-secondary degrees. More recently, Hyman (2018) studies the TAA program using a random caseworker IV design but finds no effects on the attainment of formal degrees.

[6]Jacobson, LaLonde, and Sullivan (2005a) estimate the returns to community college for displaced workers using a fixed-effects regression model with controls for worker observables and time-trends. Our IV results reveal the importance of accounting for workers' *un*observed job opportunities because injured workers only reskill if they cannot find jobs otherwise.

equilibrium considerations.

Third, our cost-benefit calculations show large returns to reskilling middle-aged workers. These findings contrast with the conventional wisdom that investing in older workers generates lower returns (Hendren and Sprung-Keyser (2020)). Our setting showcases how substantial social returns can arise when programs alleviate existing distortions in the economy – in this case, the fiscal externality of disability insurance.

Fourth, in addition to these fiscal benefits, we find that reskilling may shield injured workers from depression. These findings relate to the "deaths of despair" crisis documented by Case and Deaton (2015), in which midlife economic hardship has led to rising drug overdoses and mortality. Sullivan and Von Wachter (2009) find that job displacement from a mass layoff increases mortality, which Browning and Heinesen (2012) link to drug abuse and mental illness. Pierce and Schott (2020) show that rising import competition increases fatal drug overdoses in the US, especially among white males. Our findings for injuries and reskilling highlight that it is the lack of career prospects – not the injuries or the temporary loss of employment – that makes workers depressed. More generally, we provide the first study of the health benefits of reskilling.

Fifth, our study is inspired by human capital models featuring multidimensional ability (Sanders and Taber (2012); Traiberman (2019); Lise and Postel-Vinay (2020); Adda and Dustmann (2023)). In particular, we interpret work accidents as shocks to workers' physical abilities that induce them to invest in cognitive skills. We provide additional empirical evidence validating this mechanism for the impact of work accidents on human capital investment. First, work accidents only induce human capital investment if they decrease workers' earning capacity. Second, workers do not invest in human capital after cognitive injuries. Third, injured workers do not benefit from access to degrees with physical demands similar to their previous jobs. Finally, human capital investments help workers switch from physical to cognitive occupations. Our evidence is consistent with Gensowski et al. (2019), who show that physical disability from childhood makes individuals more likely to later obtain a university degree and work in white-collar jobs. Taken together, we provide causal evidence for some key mechanisms in human capital theories.

Finally, our results speak to the literature on general versus specific skills. For example, general skills may be more robust to shifts in labor demand or unforeseen health shocks than specific skills. They may yield a lower return than vocational degrees immediately after graduation, but in the longer run, they may overtake vocational degrees as structural change potentially devalues such degrees. For example, Hanushek et al. (2017) compare income and employment over the life cycle for workers with vocational versus higher education in 18 countries and find evidence for such a trade-off. Deming and Noray (2020) find a similar trade-off across higher education degrees as STEM degrees are immediately very valuable, but in the long term, their skills depreciate due to technological change. Our findings contribute to this literature by providing evidence for the vulnerability of vocational degrees to health shocks.

2 Institutional Setting and Data

In this section, we outline the Danish institutional setting, highlighting the features relevant to this study and describing our data sources.

2.1 Institutional Features

Denmark is known for its welfare state and flexicurity model. In brief, the government provides health care and education free of charge. Firms can hire and fire workers with relative ease, and displaced individuals are supported by generous transfers from the government.[7] The income support requires individuals to adhere to an expansive set of active labor market policies. We thus study injured workers with strong conditions for investing in human capital, as their health and time off are well-insured, and education is free. For a recent description of the Danish flexicurity system and comparison to the US context, see Kreiner and Svarer (2022).[8]

[7] Labor regulations are similarly flexible in Denmark and the United States (Botero et al. (2004)).

[8] The environment for injured workers is more similar in Denmark and the United States because U.S. workers' compensation covers the medical costs of workplace injuries and often provides tuition and income support for reskilling (Department of Industrial Relations (2022)).

2.1.1 Work Accidents

Work accidents are sudden occurrences in the course of work, leading to occupational injury. The law mandates that employers report work accidents within 14 days of occurrence.[9]

Work accidents differ from *occupational diseases*, which are contracted slowly due to ongoing exposure during work. For example, a mining collapse is a work accident, whereas miner's lung is an occupational disease. Our empirical analysis focuses on work accidents, whose discrete and unexpected timing lends itself to event studies.

The Labor Market Insurance (Arbejdsmarkedets Erhvervssikring [AES]) assesses whether a work injury claim qualifies for compensation. Workers' compensation requires that the injury has lasting effects. The assessment is based on two metrics, *personal impairment* and *earning capacity loss*, which also form the basis of workers' compensation in the United States (Barth (2003)). Personal impairment is based solely on the injury diagnosis and does not consider the worker's occupation, age, or earnings. To determine the earning capacity loss caused by an injury, the AES employs a team of industry specialists to estimate the loss of work capacity in the worker's occupation. Section 3 characterizes the type, severity, and duration of injuries that cause loss of earnings capacity. A claim qualifies for compensation if the personal impairment rate exceeds 5% or the earning capacity loss exceeds 15%.[10] The compensations are paid as one-time transfers and do not depend on the receipt of other government transfers, including disability insurance.[11] Each year, AES pays between 3 and 5 billion DKK in compensation for work accidents, equivalent to 0.15%-0.25% of GDP. Section 3.1 describes the prevalences of work accidents across occupations.

[9]Workers, unions, or medical professionals may also report the accidents within one year of occurrence.

[10]For example, the personal impairment from a tennis elbow is rated at 5%, while the earning capacity loss of a construction worker from a herniated disc is estimated at around 35%.

[11]For earning capacity losses above 50%, the additional compensations are paid in monthly installments.

2.1.2 Health Care

Healthcare in Denmark is funded by the government and available free of charge to all residents, regardless of employment status. The universal and free healthcare system provides workers with the ideal conditions to seek care for injuries and alleviates a common concern in the literature that individuals select into healthcare based on socioeconomic conditions (Currie and Madrian (1999)).[12]

2.1.3 Human Capital Investment

Upon completion of primary school (1st-9th grade), Danish students can enroll in high school or pursue a vocational degree, lasting three to four years. Vocational degrees target specific occupations, whereas high school is a stepping-stone to higher education. Higher education consists of three- to four-year bachelor's degrees, many of which are extended by two-year master's programs. Individuals may also take non-degree courses at the primary, secondary, vocational, and higher levels.

Because work accidents happen in physical occupations, most injured workers have a vocational degree or primary school as their highest educational attainment (Table 2). While high school is the main track to higher education, a subset of vocational degrees provides access to specific higher degrees. For example, a vocational degree in carpentry gives access to the bachelor's program in Construction Architecture. We describe the vocational degrees and their access to higher education in Section 4.1.

The fact that vocational degrees vary in their access to higher education is a shared institutional feature of many OECD countries, including all major European nations (OECD (2023b)).[13] Furthermore, the Danish education system follows the principles of the Bologna Process, which outlines a common structure for higher education in all

[12]The healthcare coverage of injured workers is more similar in Denmark and the United States because workers' compensation in the US covers medical costs for workplace injuries.

[13]OECD countries in which vocational degrees vary in their access to higher education include Belgium, Costa Rica, Denmark, France, Germany, Greece, Hungary, Iceland, Israel, Italy, Netherlands, Poland, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, and United Kingdom (OECD (2023b)). The International Standard Classification of Education (ISCED) subcategories 353 and 354 distinguish between vocational degrees without and with direct access to higher education.

European countries (Zahavi and Friedman (2019)).

2.1.4 Government Transfers

Disability insurance is the most relevant transfer program for injured workers in Denmark. Disability benefits are set at 19,000 DKK (2,700 USD) per month, equivalent to 50-80% of injured workers' prior earnings. To receive disability benefits, workers must be medically disabled from work. Disability benefits are paid monthly until retirement age. In terms of eligibility criteria, replacement rates, and benefit duration, the Danish disability insurance matches the Social Security Disability Insurance (SSDI) in the United States (Krueger and Meyer (2002); Autor and Duggan (2003); Reno, Thompson Williams, and Sengupta (2003)).[14]

Injured workers may receive *rehabilitation benefits* to participate in formal education or undergo retraining at a firm. The benefits are set at 19,000 DKK per month, identical to disability insurance. To claim rehabilitation benefits, a worker must be limited in his ability to work at his current skill set and have a realistic chance that reskilling could lead to sustainable employment (Ramboll (2015)). We use the term *reskilling benefits* to refer to rehabilitation benefits for formal education.[15]

If not offered rehabilitation benefits, students are eligible for *State Education Support* (SU) set at 6,400 DKK (900 USD) per month, equivalent to 15-30% of injured workers' prior earnings (one third of disability or rehabilitation benefits).[16]

Unemployed workers may claim *unemployment benefits* (if members of an unemployment insurance fund, which most injured workers are) or *cash assistance.* Unemployment benefits are set at a maximum of 19,000 DKK per month, identical to disability and rehabilitation benefits. To claim the benefits, the workers must meet with a caseworker,

[14]One difference is that there is no offset for workers' compensation in Denmark. SSDI caps the total wage replacement at 80% (Khan, Rutledge, Sanzenbacher, et al. (2017)).

[15]Reskilling benefits mirrors policies in the US, such as the vocational rehabilitation benefits of Workers' Compensation or the transfer component of Trade Adjustment Assistance (TAA). For example, TAA extends UI benefits for trade-displaced workers who enroll in school (Hyman (2018)).

[16]Disabled workers may apply for an additional Special Education Support of 5,000-9,000 DKK per month, equivalent to 15-30% prior earnings of injured workers, although these transfers are rarely granted in practice (Ramboll (2015)).

who monitors job search and assigns training programs. Individuals who are temporarily ill may claim *sickness benefits* instead of unemployment benefits.

The transfer programs are mutually exclusive, such that a worker can at most be on one program (DI, rehabilitation, SU, UI, etc.) at a time.

2.2 Data Sources

This section describes our sources of data. Our starting point is an administrative register of work injury claims in Denmark. We link the injuries to a host of registers at Statistics Denmark, providing detailed information about the health, human capital investments, government transfers, and employment of individuals from 1995 to 2017.

2.2.1 Work Accidents

Our data on work accidents come from the administrative registers of the AES, the entity responsible for handling injury claims under the Workers' Compensation Act of Denmark.

In evaluating the injury claims, the AES records detailed information on the accidents, including the injury type (e.g., bone fracture), placement on the body (e.g., arm), and cause of the accident (e.g., collision with a machine). The *Industrial Injury Register* (Arbejdsskaderegisteret) collects this information, together with the timing, assessed earning capacity loss, personal impairment, and compensations, of all work injuries.[17]

2.2.2 Health Care

We link three administrative registers of the healthcare utilization of individuals in Denmark.

The *National Patient Registry* (Landspatientregisteret) covers all hospitalizations (inpatient and outpatient), in both private and public hospitals, with detailed diagnosis codes. The *Health Insurance Registry* (Sygesikringsstatistik) covers all individual contacts with primary-care physicians and medical-care specialists outside of hospitals. The

[17]Leth-Petersen and Rotger (2009) use the register to study whiplash claims.

Prescription Drug Database (LMDB) covers all prescribed drugs that were purchased in Denmark.[18]

Combining the three registers, we observe the universe of transactions for every person within the Danish healthcare system, including hospitalizations, doctor's visits, and prescription drug purchases from 1995 to 2017.[19]

2.2.3 Human Capital Investment

We measure human capital investments using administrative registers that cover all participations in formal degrees and courses in Denmark.

The *Education Register* (UDDA) records enrollment in and completion of formal degrees. The register contains six-digit program codes covering basic education (primary and secondary school), vocational programs (e.g., a vocational degree in carpentry), and post-secondary programs (e.g., a bachelor's degree in Construction Architecture).

The *Course Participant Register* (VEUV) records enrollment in and completion of non-degree courses at the basic (e.g., a Danish language course), vocational (e.g., a certificate course in crane operations), and post-secondary (e.g., a master's course in computer programming) levels. The courses are classified according to five-digit codes. The register covers courses eligible for government subsidies and records all attendees regardless of their funding source.[20]

2.2.4 Government Transfers

The *Danish Register for Evaluation of Marginalization* (DREAM) records social transfers to individuals, including benefits for disability, rehabilitation, education, unemployment, and public pensions.

[18]In Denmark, 90% of medications are subject to prescriptions (Fadlon and Nielsen (2019)). Prescription drugs include, for example, painkillers and opioids.

[19]Fadlon and Nielsen (2019) use the registers to study how family networks shape health behaviors.

[20]In 2010, about 642,000 Danes (out of a labor force of 2.7 million) participated in courses recorded in the Course Participant Register.

2.2.5 Matched Employer-Employee Data

Our data on workers and employers come from the *Integrated Database for Labor Market Research* (IDA). The database records the earnings, hours, wage rates, and occupations of workers in Denmark. Workers are linked to establishments and firms in week 48 of each year. Occupations are classified according to a six-digit version of the ISCO nomenclature, which we link to the Occupational Information Network (O*NET) on the task contents of occupations.[21]

2.2.6 Sociodemographics

The *Population Register* (POP) records the age, gender, and family relations of all individuals in Denmark.

3 Work Accidents

In this section, we establish how work accidents affect workers' health, earnings, and human capital investments. These results set the stage for our main analysis in Sections 4 and 5, evaluating whether reskilling helps injured workers get back to work.

In brief, we document that work accidents occur quasi-randomly within occupations and cause persistent damage to the health and earnings of workers. Second, injured workers who invest in human capital overwhelmingly enroll in higher degrees. Finally, human capital investment decreases steeply with age.

3.1 Incidence on Occupations

Every year, about 0.6% of workers in Denmark are injured in a work accident. For comparison, this number is slightly higher than the risk of being displaced in a mass layoff, a shock to workers frequently studied in the labor literature (Jacobson, LaLonde, and Sullivan (1993)).[22,23]

[21]We link O*NET to ISCO codes using the crosswalk of Hardy, Keister, and Lewandowski (2018).

[22]Appendix Figure A.1 shows the time series of work accidents and mass layoffs in Denmark.

[23]In the United States, both the risk of being injured in a workplace accident and being displaced in a mass layoff is substantially higher than in Denmark. Official records from the Bureau of Labor Statistics

Table 1 lists the five occupations with the highest rate of work accidents. The ranking shows that accidents predominantly occur in physically demanding jobs, such as building and construction. For example, measuring the physical requirements of occupations using the O*NET index of *"Physical Ability Requirements"*, we find that 84% of all work injuries occur in the 50% most physical occupations.[24]

[Table 1 around here]

3.2 Impact on Workers

This section examines the outcomes of workers before and after they experience a work accident. We make a series of sample cuts to hone in on a set of well-defined injury events.

First, we use the AES data to focus on work accidents that caused a loss to workers' earning capacities.[25] Second, we focus on work accidents with a physical impact on workers, and thus exclude psychological shocks.[26] Third, we focus on workers with stable employment before the injury, defined as full-time employment in the three years leading up to the accident. Finally, we exclude military workers because they represent a distinct set of work accidents and labor market prospects. Appendix Table A.2 shows that these additional sample restrictions do not affect the severity of the injuries considered in the analysis.

Table 2 shows characteristics of workers in the year before experiencing an accident ("Injury" column). The typical injured worker is a 43-year-old man who has completed a vocational degree. Before the accident, the worker was employed in a physically demanding occupation with low cognitive requirements.

indicate an incidence rate of around 1.6% for mass layoffs and around 2.9% for workplace accidents (BLS (2023); CDC (2023)), showing that the risk of workplace accidents is even higher compared to mass layoffs in the US.

[24] *Physical Ability* is defined as the average importance of Static Strength, Explosive Strength, Dynamic Strength, Trunk Strength, and Stamina, as measured by O*NET.

[25] The assessments by AES are done upfront before any eventual reskilling or re-employment of workers.

[26] In Section 3.3, we compare our main estimates to workers' human capital investment after cognitive injuries or injuries that do not cause loss of earning capacity.

The next columns report characteristics of workers who do not experience an accident in the event year ("No Injury"). The "Match" column matches the workers to the characteristics of the "Injury" workers. That is, for each injured worker, we find a control worker with the same occupation (three-digit ISCO), industry (two-digit NACE), level of education, age, and gender in the year before the work accident. The last column reports the standardized mean differences between the "Injury" and "Match" workers, where absolute values above 25% is a standard threshold for assessing imbalance (Stuart and Rubin (2008)).

The table shows that the "Injury" and "Match" workers are balanced on all covariates, including a host of outcomes we do not match on, such as their earnings and work hours (the *Employment* panel), savings and debt behaviors (*Wealth*), residence and family situations (*Demographics*), and access to higher education (*Reskilling*). Furthermore, Appendix Table A.3 shows that this balance is already obtained when only matching workers' occupations.[27] The robust similarity between the "Injury" and "Match" workers supports the identifying assumption that work accidents are quasi-random within occupations such that workers with and without injuries are valid comparisons.[28]

The *Injury* panel shows the severity of the injuries, as assessed by AES.[29] The average injury in our sample reduces workers' earning capacity by 37% and causes a personal impairment of 12%.

[Table 2 around here]

We study the simple differences-in-differences in outcomes Y between the injured workers ($I = 1$) and their matches ($I = 0$) around work accidents, indexed to the year before the accident:

$$Y_{it} = \beta_1 I_{ie} + \sum_k \beta_{0k} \mathbf{1}_{\{t=e+k\}} + \sum_{k \neq -1} \beta_{1k} I_{ie} \mathbf{1}_{\{t=e+k\}} + \varepsilon_{it}, \tag{1}$$

[27] Work accidents are more prevalent in physical occupations, cf. Table 1.

[28] Altonji, Elder, and Taber (2005) and Oster (2019) provide conditions under which the similarity of workers on observable outcomes supports the quasi-exogeneity of work accidents.

[29] Section 2.2.1 describes the severity metrics.

where $\mathbf{1}_{\{t=e+k\}}$ are event-time dummies that switch on if the event year e occurred k years ago, and β_{1k} are our coefficients of interest, identifying the causal effects of work accidents under parallel trends. We estimate Equation (1) by OLS and cluster the standard errors at the match-cell level.

Three connections to the recent literature on differences-in-differences designs deserve notice (Callaway and Sant'Anna (2021); Roth et al. (2022)). First, by matching treated and control workers before each event year e, we ensure Equation (1) identifies positively-weighted averages of causal effects under parallel trends. Second, recent estimators often use later-treated or never-treated units as the control group. However, because treatment in our case happens at the workplace, later-treated and never-treated workers are implicitly selected on their post-event employment outcomes.[30] For this reason, we prefer to match workers before the accidents and not condition the control group on post-event outcomes. That said, because workers have minimal risk of severe work accidents before and after the event year, our control workers are overwhelmingly never-treated units.[31] Appendix Figure A.5 verifies that our baseline estimates are virtually identical to the estimators of Callaway and Sant'Anna (2021), Sun and Abraham (2021), and De Chaisemartin and d'Haultfoeuille (2022a) implemented on never-treated units. Finally, in our main analysis of human capital investment (Sections 4 and 5), we compare injured workers who differ in their access to education, where the non-injured match workers merely serve as placebo checks.

Appendix Figure A.6 shows that the differences-in-differences estimates are robust to relaxing the covariates that the treatment and control workers are required to match on before the events. The robustness corroborates that our baseline estimates identify the causal impacts of work accidents.

[30]Workers must be employed to get into a workplace accident. So, for example, that means "later-treater" workers must remain employed in the post-period. By contrast, we do not impose such a condition on the treatment group because an important consequence of work accidents is loss of employment.

[31]Appendix Figure A.3 plots the incidence of work accidents for the treated and control workers.

3.2.1 Health and Income

Figure 1 shows the impact of work accidents on the health and income of workers. The figure delivers four insights. First, before experiencing a work accident, workers have a similar evolution of health and earnings as other workers in their occupations. The flat pre-trends support the assumption that work accidents happen quasi-randomly within occupations. Second, work accidents severely shock workers' health, with days spent in the hospital spiking for two years after the accidents (Panel (a)).[32] Third, work accidents cause persistent damage to workers. Workers' use of painkiller prescriptions jumps by 25 percentage points after the injuries (Panel (b)), and their labor earnings suffer a persistent loss of about 40% (Panel (c)).[33] For comparison, Appendix Figure A.2 shows that work accidents cause more persistent losses of earnings than mass layoffs. Finally, although public transfers cover some of the economic losses, work accidents are a severe shock to the well-being of workers. After the accidents, workers' labor income (including transfers) decreases by about 30% (Panel (c)),[34] and the share of workers who use antidepressants increases by about 10 percentage points (Panel (d)).

[Figure 1 around here]

3.2.2 Human Capital Investment

Figure 2 plots the participation of workers in degree and non-degree courses. For example, *higher non-degree* includes university courses in computer programming, and *higher degree* includes bachelor's programs in construction engineering. The activity is measured in full-time equivalents. The *higher degree* line shows that, two years after the accident, 8% of injured workers are enrolled in a post-secondary degree.

The figure focuses on workers whose initial education provides direct access to higher degrees because these workers are better positioned to invest in human capital upon in-

[32] The workers visit the doctor's office seven times in the year after the accident.

[33] Ten years after the accidents, the workers pay two more visits to the doctor's office per year.

[34] Appendix Figure A.4 splits the transfers by program. The figure shows that sickness benefits spike right after the injury, then rehabilitation benefits become relevant in an intermediate period, before DI becomes the dominant program over time.

jury.[35] Appendix Figure A.7 shows the plots separately for each initial level of education, confirming that human capital investments are made overwhelmingly by workers with direct access to higher education.[36] In Section 4.1, we investigate the causal role of access to education in the reskilling of injured workers.

Figure 2 reveals two findings. First, most workers do not invest in human capital after losing work abilities. Ten years after work accidents, about 13% of the workers have enrolled in a degree at any level, and take-up of non-degree courses is negligible (workers have participated in 1% of a full year's worth of courses). Second, workers who invest overwhelmingly enroll in higher degrees, lasting about four years. In particular, higher degrees constitute 83% of total human capital investment after work accidents. Appendix Figure A.8 shows that over 80% of injured workers who pursue higher education also complete their degrees.[37] In summary, Figure 2 shows that workers make long-term and advanced investments in human capital after losing abilities. By contrast, shorter training courses, including those targeting high-skill jobs, are not attractive for injured workers.

In Appendix B, we cast light on the types of higher degrees injured workers invest in. To do so, we link each degree to its target occupations, allowing us to compare characteristics of the degrees to workers' initial jobs.[38] The classification of degrees delivers two insights. First, workers invest in degrees that target occupations that are less physically demanding than their initial job (Figure B.1.(a)). Second, when investing in human capital, workers target degrees that build on their work experiences (Figure B.1.(b)). For

[35] Workers with access to higher education consist of high school graduates and workers whose vocational training provides access to specific higher degrees. Because work accidents happen in physical occupations (and most high school graduates continue to earn a post-secondary degree), 95% of injured workers with access to higher education have a vocational degree as their highest educational attainment (Table A.4). Section 2.1.3 describes the Danish educational system, and Appendix Table A.5 lists the vocational degrees and their access to higher education.

[36] For example, ten years after the work accidents, two-thirds of the total impact on the completion of higher degrees are driven by the one-third of workers who initially had direct access to higher education (Table A.4).

[37] The completion rate among injured workers is similar to the average rate in the student population. In particular, the average completion rate of full-time students in bachelor's degrees is 81% in Denmark and 78% in the United States OECD (2023a, Table A9.1).

[38] For example, we link the bachelor's degree "4087 Construction Architecture" to the target occupation "2142 Construction Architects." Appendix B explains the linking methodology.

example, many construction workers obtain a bachelor's degree in construction engineering after work accidents.[39]

[Figure 2 around here]

In Figure 3, we split the enrollment rates in higher degrees by the age at which workers experience a work accident. The plot shows that human capital investment decreases steeply with age. In particular, workers older than 50 do not invest in higher education after work accidents.[40] By contrast, almost half of the youngest workers aged 20 to 25 take up higher education after injuries. The pattern is consistent with a lifecycle model in which forward-looking workers consider if they have enough remaining working years to recoup an educational investment. We return to these cost-benefit considerations in Section 5.3 after having estimated the causal effects of reskilling.

[Figure 3 around here]

3.3 Mechanisms

We interpret work accidents as shocks to workers' physical abilities. The interpretation allows us to tie our reduced-form evidence to theories of human capital investment that feature multidimensional ability (Sanders and Taber (2012)). Appendix Figures A.9-A.11 provide empirical evidence for this mechanism for the impact of work accidents on human capital investment.

First, to assess the importance of lost *ability* for human capital investment, we exploit that the AES assesses the loss of earnings capacity caused by each work accident.[41] Figure A.9 shows that work accidents *only* generate human capital investment if they cause a loss of earnings capacity. To further distinguish the role of *ability* loss from the

[39]Workers target degrees that belong to the same *career cluster* as their original jobs. Career clusters are defined as *"occupations in the same field of work that require similar skills"* (O*NET). The career clusters are developed by O*NET to help *"focus education plans towards obtaining the necessary knowledge, competencies, and training for success in a particular career pathway."* For example, carpentry and construction architecture belong to the career cluster *Architecture & Construction*.

[40]Jacobson, LaLonde, and Sullivan (2005b) document a similar age gradient in the retraining decisions of displaced workers.

[41]Section 2.2 details the assessment process.

effects of *job* loss, Appendix Figure A.11 studies workers' pursuit of education after mass layoffs. The figure shows that workers generally do not invest in human capital after job displacement.[42]

Second, to examine whether human capital investment differs for *cognitive* versus *physical* injuries, we use diagnosis codes to identify permanent brain damage. The analysis first reveals that cognitive injuries are rare among work accidents. Yet, zooming in on these rare events, Figure A.10 shows that workers do not invest in human capital after cognitive injuries.

In summary, our findings provide direct evidence for a key mechanism in human capital theories by showing how shocks to workers' physical abilities induce them to invest in cognitive skills.

4 Human Capital Investment

In this section, we study whether human capital investment helps injured workers return to work. Identifying the causal effects of these investments is challenging because, as we have documented, workers reskill based on the severity of their injuries (Figure A.9), their expected payoffs from education (Figures 3 and A.10), and other factors related to their counterfactual job opportunities without reskilling.

To identify the causal effect of human capital investment, we exploit that some initial vocational degrees provide direct access to post-secondary programs in Denmark, but others do not. The differences in admission criteria allow us to compare otherwise similar workers who differ in their access to higher education upon injury.

In Section 4.1, we identify similar workers who differ in their eligibility for higher education. We conduct several placebo checks of the comparability of these workers. In Section 4.2, we use the workers to estimate the reduced-form impacts of access to higher education for injured workers. Section 4.3 estimates the potential outcomes of injured

[42]Minaya, Moore, and Scott-Clayton (2023) replicates this finding in the US, showing that very few workers enroll in college after job displacement.

workers with and without reskilling. Finally, in Section 4.4, we conduct a cost-benefit analysis of providing access to higher education for injured workers.

4.1 Identification Strategy

4.1.1 Access to Higher Education

In Denmark, some initial vocational degrees provide direct access to higher education programs, but others do not. For example, vocational training in carpentry gives direct access to the bachelor's program in Construction Architecture. By contrast, landscape gardening (an otherwise similar vocational degree to carpentry) does not grant access to post-secondary degrees, and workers must complete three years of high school before any higher education.[43]

In Appendix Table A.5, we provide a list of vocational degrees and their access to higher-education programs in Denmark. The injured workers whose vocational training provides access to higher education 70% craft workers (e.g., carpenters), 10% care workers (e.g., nurse assistants), 10% retail workers (e.g., sales assistants), and 10% food service workers (e.g., chefs); see Appendix Table A.6 for an overview.

Care workers are peculiar because their higher-education programs target jobs with physical demands similar to their original jobs.[44] Motivated by the critical importance of the physical intensity of target jobs (Figure B.1.(a)), we divide our analysis into two parts. In the main text, we focus on the craft workers, who all have access to degrees with lower physical intensity. In Appendix D, we study the care workers. We find that care workers invest significantly less in human capital after accidents and that their access to higher education does not help their employment prospects after injuries. The findings for care workers underscore that higher education only helps injured workers if the programs target jobs that are less physically demanding.[45]

[43] As Section 2.1.3 describes, the Danish educational system is representative of many OECD countries. In particular, the fact that vocational degrees vary in their access to higher education is a shared institutional feature of 18 OECD countries, including all major European nations (OECD (2023b)).

[44] For example, nursing assistants are eligible for the bachelor's program in nursing. However, because most nurses end up in physically demanding hospital jobs, these educational opportunities may not provide a better way back to work.

[45] Appendix D provides evidence that the different impacts among care and craft workers do not reflect

4.1.2 Finding Comparable Workers

The institutional rigidities of the Danish educational system allow us to identify comparable workers in similar occupations and with similar amounts of schooling who differ in their access to higher education only due to their different vocational specializations.[46] To find these workers, we implement an inverse probability weighting (IPW) strategy detailed in Appendix C. The reweighing allows us to compare workers of similar demographics, years of schooling, earnings, occupations, and injuries who differ in their access to higher education. Table 3 shows that the "Access" and "No Access, IPW" workers balance on these covariates together with a host of characteristics not targeted by the IPW method. We comment on these characteristics in Section 4.1.3 below, which provides additional placebo checks of the comparability of the worker groups.

[Table 3 around here]

Importantly, while the IPW ensures that the worker groups are comparable before the injuries, Appendix C.1 shows our difference-in-differences estimates in Sections 4.1.4 and 4.2 are robust to the IPW method. In particular, Appendix Figures C.1-C.2 show that the estimates are similar if we do not reweigh on the covariates in Table 3, and instead use the "No Access, Raw" workers as the control group, only balancing on the immediate severity of the injuries and whether the workers are employed in the public sector.[47] These results highlight that our conclusions for the effects of reskilling do not hinge on the IPW selection of the "No Access" control group.

gender differences in reskilling behaviors.

[46]The institutional differences in access to higher education are widely believed to reflect rigidities of the current educational system (Regeringen (2014)). For example, under current rules, landscape gardeners are not eligible for a bachelor's degree in landscape architecture. Indeed, a stated goal of the Danish government is to *"make it easier for vocationally-trained workers to take a relevant higher education without first going through high school"* (Regeringen (2022)). Our reduced-form evidence in Section 4.2 informs this policy proposal.

[47]Public sector employees have stronger job security immediately following work accidents.

4.1.3 Placebo Checks

The identifying assumption of our analysis is that the "Access" and "No Access" workers would fare similarly after work accidents if not for their different access to higher education. In this section, we assess the validity of this identifying assumption.

First, Table 3 shows that the "Access" and "No Access" workers are similar in a host of outcomes not targeted by the IPW method, including their career trajectories, savings and debt behaviors, residence and family situations, and commuting distances to reskilling facilities leading up to the accidents. These similarities suggest that the workers had not arranged their lives after the need to reskill or change tracks.

Second, Appendix Table A.7 shows that workers with and without access to higher education were also similar at age 16, the time at which they decided on their vocational specializations. In particular, the workers had similar grades from primary school, were equally likely to have a youth job, and their parents had similar education and wealth. These similarities suggest that individuals who select vocational degrees that grant access to higher education are not more capable nor come from more resourceful backgrounds.[48]

Third, in all figures, we report the outcomes of the match workers around their "placebo" accident events. The "No Injury" lines of Figures 5 and 6.(a) show that the "Access" and "No Access" workers have similar human capital investments and labor earnings if not injured by a work accident.[49]

Fourth, workers with different access to higher education experience injuries of similar severity. The *Injury* panel of Table 3 shows that the workers face similar risks of accidents and experience similarly severe injuries.[50] Figure 4 further validates that the work

[48]Workers' initial choice of vocational degrees may not anticipate the need for reskilling after severe injuries later in life, as these are low-probability events that occur on average 27 years after the choice of vocational degrees. Throughout their careers, workers have a 4% risk of experiencing a physical injury that causes loss of earning capacity. The average injury occurs at age 43 (cf. Table 2), on average 27 years after the choice of vocational degrees.

[49]The similar labor earnings of non-injured workers do not reflect that the workers remain static in their employment tracks: ten years after their placebo events, 76 percent have changed their employer, and average earnings are 30 percent lower, reflecting that some workers exit employment. Work accidents are, however, an important push toward reskilling, as only 1.5 percent of non-injured workers enroll in higher education during the ten-year post-period. Appendix Figure A.17.(b) reports the labor supply of non-injured workers.

[50]Table A.8 further shows that the workers experience similar types of detailed injuries, including the

accidents cause similar health impacts for the groups immediately after the injuries. In the year of the work accidents, the "Access" and "No Access" workers spend about six days in the hospital. The hospitalization rates then decline similarly in the years after the work accidents.

[Figure 4 around here]

Fifth, in Appendix Figure A.13, we study milder work accidents that only cause temporary injuries to workers.[51] Panel (a) first shows that these temporary injuries do not induce workers to enroll in higher education, confirming that workers only reskill if permanently disabled. Panel (b) then shows that workers with and without access to higher education fare similarly in the labor market after these temporary injuries.

Finally, in Appendix Figure A.14, we focus on workers older than 55 who do not invest in human capital despite being eligible for higher education (Figure 3). The figure shows that these older workers fare similarly after work accidents.

Taken together, these placebo checks counter the potential identification threat that workers with access to higher education may perform better in the labor market regardless of reskilling. Instead, the evidence presented in this section supports the exclusion restriction that access to higher education helps injured workers by enabling them to reskill.

4.1.4 Relevance for Human Capital Investment

Having established the comparability of the workers with and without access to higher education, we now turn to the first stage, studying their differences in reskilling after injuries.

Figure 5 shows the pursuit of higher degrees around work accidents by workers' eligibility for higher education. The plots are the differences-in-differences in outcomes Y

cause of injury events and affected body parts.

[51] We measure temporary injuries as accepted work accident claims that AES assesses did not cause a *permanent* loss of earning capacity or personal impairment to the worker.

between the access groups $A \in \{0,1\}$, indexed to year before the accident:

$$Y_{it} = \theta_1 A_{ie} + \sum_k \theta_{0k} \mathbf{1}_{\{t=e+k\}} + \sum_{k \neq -1} \theta_{1k} A_{ie} \mathbf{1}_{\{t=e+k\}} + \varepsilon_{it}, \tag{2}$$

where θ_{1k} are our coefficients of interest, identifying the causal effects of access to higher education around work accidents. We estimate Equation (2) by OLS, weighing the workers as in the "IPW" column of Table 3.

Figure 5 shows that access to higher education is crucial for injured workers' investments in human capital. The "Access" group invests more in human capital, but only if hit by a work injury. Ten years after work accidents, the workers with access to higher education are 10% more likely to have pursued a higher degree.[52]

[Figure 5 around here]

4.2 Reduced-Form Effects

In this section, we use the "Access" and "No Access" groups to study the impact of access to higher education on the employment of injured workers.

Figure 6 compares the workers' labor earnings around work accidents. After an initial lock-in period, workers with access to higher education have permanently higher earnings. The differences in earnings represent around 10% of the workers' earnings before the accident. To be clear, this is a large reduced-form effect, considering that the first-stage effect on reskilling is also around 10% (Figure 5.(b)).

Where do the large effects on labor earnings come from? In Appendix Figure A.15, we investigate the labor-supply choices that generate the earnings differences. The figure shows that access to education helps injured workers move from disability benefits to formal employment. Ten years after work accidents, workers with access to higher education are 10% less likely to receive disability benefits (Panel (a) of Figure A.15) and 10% more likely to be employed (Panel (b) of Figure A.15). By contrast, we do not find that access

[52] Figure A.12 shows that the access policy does not affect workers' take-up of other education.

to education influences workers' take-up of non-means-tested pensions (Appendix Figure A.16).

[Figure 6 around here]

4.3 Potential Outcomes

To understand the counterfactuals that generate the reduced-form effects, we estimate the potential outcomes of injured workers with and without reskilling. We identify these counterfactuals for the workers who comply with the access policy by reskilling after injuries. Appendix Tables A.9-A.10 characterize the compliers, showing they are younger, more likely female, received better grades in primary school, have higher-educated parents, and live closer to reskilling facilities.[53]

We convert the reduced-form effects from Section 4.2 into potential outcomes for the compliers by assuming that *access* to education affects workers only if they pursue the programs.[54,55] Hence, our treatment variable D is equal to 1 if the worker pursues a higher degree within ten years after the accident.

Let $Y_i(D_i)$ denote the potential outcome of worker i with and without higher education, and D_{Ai} denote his potential education depending on his access to higher education $A \in \{0, 1\}$. Following Abadie (2002), the average potential outcomes of compliers are given by the Wald estimates:

$$\mathbb{E}[Y_{ik}(0)|D_{1i} > D_{0i}] = \frac{\theta_{1k}^{Y(1-D)}}{\theta_{1,10}^{(1-D)}} \tag{3}$$

$$\mathbb{E}[Y_{ik}(1)|D_{1i} > D_{0i}] = \frac{\theta_{1k}^{YD}}{\theta_{1,10}^{D}}, \tag{4}$$

[53]Section 5.1 assesses the effects of expanding the reskilling program beyond these compliers.

[54]Appendix 4.1.3 performs placebo checks that support this exclusion restriction.

[55]Mountjoy (2022) imposes a similar exclusion restriction in using commuting distance to estimate the returns to colleges. The exclusion restriction is violated if, for example, the *option value* of access to education makes workers stay in the labor force. Importantly, in our context, the eligibility for Disability Insurance does not depend on workers' access to higher education (European Commission (2023)).

where θ^Y_{1k} is the difference in outcomes between the access groups k years after the injury:

$$Y_{it} = \theta^Y_{0k} + \theta^Y_{1k} A_{ie} + \varepsilon^Y_{it} \quad \text{if} \quad t = e + k. \tag{5}$$

We estimate Equation (5) on a balanced sample, weighing the workers as in the "IPW" column of Table 3. For example, θ^D_{1k} is our first-stage estimate in Figure 5.(b), whereas θ^{YD}_{1k} and $\theta^{Y(1-D)}_{1k}$ decompose our reduced-form effects (e.g., Figures 6 and A.15) according to whether workers complete a higher education after the accidents.[56]

The idea behind Equations (3)-(4) is that access to education affects labor market outcomes exclusively by shifting compliers into higher education. Hence, by interacting the outcome variable (Y) with the higher-education treatment status (D and $1 - D$), we identify the average potential outcomes of compliers with and without higher education.

We estimate Equations (3)-(5) using two-stage least squares (TSLS) and follow Imbens and Rubin (1997) in imposing non-negativity constraints on the potential outcomes.[57]

Figure 7 shows the labor supply of injured workers with and without reskilling. The figure delivers three insights. First, reskilling keeps workers in school during the first six years after work injuries. Second, about 80% of injured workers who reskill end up finding employment. Third, if these workers do not reskill, they end up entirely on disability benefits.

[Figure 7 around here]

Table 4 reports the job characteristics of the injured workers who find employment after reskilling.[58] The table shows that higher education allows workers to reallocate from physically demanding occupations to more cognitively intense jobs. Ten years after

[56]We estimate θ^Y_{1k} as simple differences in between the access groups to recover the levels of workers' potential outcomes. Note that the simple differences (Equation (5)) and the difference-in-differences (Equation (2)) give similar point estimates of θ^Y_{1k} for our reduced-form outcomes (e.g., Figures 6 and A.15) because the "Access" and "No Access, IPW" groups are similar on the outcomes before the injury (Table 3).

[57]The constrained outcomes are within the confidence bands of the unconstrained estimates for all outcomes and time periods.

[58]Because job characteristics are measured for employed workers only, Table 4 define the treatment variable as $D \times E$, where E equals 1 if the worker has completed his degree and is employed ten years after the accident (blue area in Figure 7.(a)).

the work accident, the reskilled workers earn 25% more than before their injuries. These earnings effects are especially remarkable given that the workers were not marginalized before the injuries but earned slightly less than the median full-time worker in Denmark. The higher earnings instead fully reflect that reskilled workers transition into high-pay occupations. Indeed, a naive prediction based on average occupational pay premia would expect the reskilled workers to earn 77% more than before their injuries. Hence, although reskilling helps workers transition into cognitive and high-pay occupations, the reskilled workers still start at the bottom rungs of the pay ladders in their new occupations.

[Table 4 around here]

Figure 1.(d) showed that work accidents are a severe shock to the mental well-being of workers, whose use of antidepressants spike after injuries. Does reskilling alleviate these mental burdens of injuries? To assess this question, Figure 8 plots workers' potential use of antidepressants with and without reskilling. Strikingly, the figure shows that work accidents only make workers depressed if they cannot reskill. Furthermore, the benefits on mental health appear immediately following the accidents and generally before the income gains of reskilling in Figure 6. These results indicate that it is the lack of career prospects – and not the injuries or temporary income losses – that makes injured workers depressed.

[Figure 8 around here]

4.3.1 Potential Outcomes without Injuries

Our analysis above showed that injured workers who reskill get back to work, eventually earn more than before their injuries, and do not get depressed. The positive results probe the questions: Are these workers made *better* off by experiencing a work accident? And should these workers have been reskilled before the accidents?

To answer the first question, we compare the complier workers to the outcomes of their match workers (who are not injured in the event year). That is, we rerun Equations

(4)-(5), using outcomes of the match workers as the dependent variable. Appendix Table A.11 shows that the reskilled workers end up in very different types of occupations (less physically demanding, more cognitively intense, and with higher average pay), compared to the scenario without injury. However, in terms of lifetime income and mental well-being, the difference in scenarios is less stark. Ten years after the accidents, the workers are about 10 percentage points more likely to be employed (Appendix Figure A.17) and earn about 3% more in their jobs (Appendix Table A.11) than if they had not been injured. However, before arriving at these higher earnings, the workers undergo a period of lower income while in school. In present-discounted terms, the reskilled workers have similar lifetime income (1% lower) compared to the scenario without injury (Appendix Table A.12).[59] Furthermore, the workers' use of antidepressants is flat in both scenarios (Appendix Figure A.18). Finally, as Figure 1 showed, the injuries cause physical pain, hospitalizations, and other suffering not reflected in lifetime income. From a public perspective, the injuries are also not desirable, as the government forgoes taxes and pays tuition and benefits while the injured workers are in school (Table A.12).

To assess the second question of whether the workers should have been reskilled before their injuries, we make two adjustments to the "Injury & Reskill" scenario.[60] First, without the injuries, workers would avoid the immediate spike in sick leave and gradual increase in disability benefits following the accidents.[61] Second, the workers would not be eligible for reskilling benefits while in school.[62] Appendix Table A.12 incorporates these adjustments, showing that workers' lifetime income in the "No Injury & Reskill" scenario is very close to (0.7% higher in present-discounted values) the "No Injury" coun-

[59]If workers are constrained in smoothing their consumption over time (e.g., due to liquidity constraints, as in Chetty (2008)), the reskilling scenario with lower income while in school is less attractive for workers.

[60]See the note of Appendix Table A.12 for a detailed explanation of these adjustments.

[61]This adjustment likely overstates the lifetime income in the "No Injury & Reskill" scenario. The calculations namely make the extreme assumption that injured workers who go on sick leave (in years 0-3) or DI (in years 3 and onwards) would have experienced their match workers' outcomes without the initial work injury. By contrast, Figure A.17 shows that a smaller fraction of workers does take sick leave and DI even without the initial work accidents. We adopt the extreme assumption to clarify the robustness of our conclusion that workers should not have been reskilled before the accidents.

[62]The workers would instead receive the standard stipend (SU); see Section 2.1.4 for a description of these government transfers.

terfactual.[63,64] The reskilling of non-injured workers is also not desirable from a public perspective, as the government forgoes taxes and pays tuition and benefits while the workers are in school. In total, the government loses an additional 60 cents on each dollar spent reskilling non-injured workers (Table A.12).

In summary, our analysis shows that – even if reskilling yields high returns after severe injuries – workers who reskill are not better off by their work accidents, nor should they have been reskilled before the accidents. Instead, the large returns to reskilling reflect that the alternative for these severely injured workers is to end up on disability insurance, often resorting to taking antidepressants.

4.4 Cost-Benefit Evaluation

In this section, we use the causal estimates from Section 4.2 to conduct a cost-benefit evaluation of investing in human capital for injured workers.

To be precise, we calculate the present discounted values of providing higher education for workers who suffer a work injury at age 32, the average among our compliers. Our calculations combine the dynamic estimates from Section 4.2 with government tax and transfer rates to estimate the costs and benefits for injured workers and the government. Appendix E details our approach to the cost-benefit calculations. Notably, the estimates in this section apply to our *instrument compliers*, that is, injured workers who reskill only if they have direct access to higher education. Section 5.1 considers the effects of reskilling a broader set of injured workers.

Table 5 summarizes the costs and benefits of reskilling for workers and the government. The cost-benefit analysis delivers four takeaways. First, among compliers, providing post-secondary education for an injured worker generates a monetary surplus of about a half million USD, equivalent to a 680% return on the education expenses.[65] The investment

[63]The difference would increase to 5.5% if non-injured workers could access reskilling benefits.

[64]Again, if workers are constrained in smoothing consumption, the lower income while in school is less attractive for workers. Access to reskilling benefits would partly alleviate this disadvantage of reskilling for non-injured workers.

[65]Cost-benefit analyses sometimes inflate the direct gross cost to the government (*Educ. Transfers + Tuition* in Table 5) with a “marginal cost of public funds”, reflecting deadweight loss of taxation to

generates an internal rate of return (IRR) of 48% per year, about four times higher than conventional estimates for young or displaced workers (Kane and Rouse (1995); Heckman, Lochner, and Todd (2003); Jacobson, LaLonde, and Sullivan (2005b)).[66] Second, the remarkable social returns reflect that higher education moves injured workers from disability insurance (a liability to the government budget) to taxable high-income employment (an asset to the budget). The combination of lower transfer payments and higher tax receipts means that the government expenditure on education pays for itself four times over.[67] Third, the table shows that reskilling benefits provide substantial support for workers who reskill, amounting to 20% of their income gain from reskilling.[68,69] Finally, the table shows how a generous transfer system weakens the private incentives for workers to invest in human capital. In particular, about 68% of the higher pre-tax earnings from reskilling are countered by lower transfers and higher tax payments for workers.

[Table 5 around here]

Our main cost-benefit analysis focuses on earnings, taxes, and transfers, whose monetary values are straightforward to evaluate. In particular, Table 5 does not include the health benefits of reskilling, such as preventing depression (Figure 8). In Appendix E.1, we assess the mental health benefits using expenditures on treatment (medication and counseling) and existing estimates of the value of mental health in terms of life quality. In total, we estimate a lower bound on the added social return from mental health of $51,000 per reskilled worker, which is split $29,000 for workers and $22,000 for the government.

finance the program (Kleven and Kreiner (2006)). Applying a deadweight loss of 50% to the direct costs, as in Heckman et al. (2010), would deliver a net social return of 420%, and the total government cost (program cost and deadweight loss) would pay for itself two times over. Reskilling subsidies for injured workers pay for themselves as long as the deadweight factor is below 395%.

[66] The internal rate of return is the annual interest rate that makes an investment break even.

[67] In the terminology of Hendren and Sprung-Keyser (2020), subsidizing higher education for injured workers has an infinite Marginal Value of Public Funds (MVPF).

[68] If workers are constrained in smoothing consumption, they may particularly value the reskilling benefits, as the payments fall in years when workers are in school and have lower earnings.

[69] Policy discussions on reskilling often emphasize income support to incentivize workers to reskill. For example, TAA extends UI benefits to workers who participate in formal education in the US. Similarly, Jacobson, LaLonde, and Sullivan (2011) propose covering living expenses to support displaced workers who reskill.

By construction of our access IV, the reduced-form evidence presented in this section is relevant for policies that provide access from vocational degrees to higher education. Indeed, a stated goal of the Danish government is to *"make it easier for vocationally-trained workers to take a relevant higher education without first going through high school"* (Regeringen (2022)). Table 5 directly informs the costs and benefits of such a policy for injured workers.

However, it is worth noting that the large returns in Table 5 do not imply that able and employed workers should be encouraged to reskill. On the contrary, Section 4.3.1 showed that reskilling non-injured workers is costly to the government budget. Instead, the large public returns in Table 5 reflect that the alternative for severely injured workers is to end up on disability insurance.

Tables A.9-A.10 show that workers who respond to the access policy are younger, received better grades in primary school, have higher-educated parents, and live closer to reskilling facilities. These selection patterns beg the question of whether the large surpluses in Table 5 also apply to a broader set of injured workers. In Section 5, we evaluate such expansions of the reskilling program.

5 Policy Counterfactuals

In this section, we assess the counterfactual effects of reskilling more injured workers. Expanding reskilling programs could yield decreasing returns for at least three reasons. First, within a cohort, workers may self-select into reskilling based on their idiosyncratic returns to the program. For example, at the current level of the policy, individuals may only reskill if they cannot find jobs otherwise and are prepared for higher education.[70] Hence, expanding reskilling to more workers could entail lower returns. Second, expanding the program could imply rolling it out to older workers with fewer working years left to reap the labor market returns to new skills. Finally, large expansions of the reskilling

[70] Indeed, Tables A.9-A.10 show that compliers to the access policy have better grades from primary school and higher-educated parents. Furthermore, Figure 7 shows that the alternative for these workers is to end up entirely on disability insurance.

programs could have equilibrium impacts on labor markets.

In Sections 5.1 and 5.2, we assess the first two sources of decreasing returns by estimating how marginal treatment effects of reskilling vary within and across cohorts of injured workers. In Section 5.3, we use these estimates to evaluate the partial-equilibrium effects of changing the rates of reskilling for injured workers. Finally, in Appendix F, we show that the optimal rates of reskilling are robust to general equilibrium considerations.

5.1 Marginal Treatment Effects

In this section, we estimate the returns to reskilling for workers at the margin of participation at different levels of program expansion (p). To do so, we estimate marginal treatment effects (MTEs) of reskilling by interacting our "access to higher education" instrument with workers' age and commuting distances to higher education facilities.[71]

The MTEs identify heterogeneous returns by workers' *unobserved* resistance to reskilling. This strategy complements our earlier analysis of *observable* heterogeneity, including that the positive returns to reskilling concentrate on physical injuries that cause loss of earning capacity (Section 3.3), degrees that provide pathways to less physical jobs (Appendix D), and younger workers (Section 4.4).[72]

Following Heckman and Vytlacil (2007), our MTE strategy aims to estimate a continuum of treatment effects according to the "encouragement" (based on an observable propensity score) needed for workers to take up the treatment:

$$p(\text{Reskill}_i = 1) = \mu(Z_i) \tag{6}$$

$$\text{MTE}(p) = \frac{\partial \mathbb{E}[Y_i | \hat{p}_i = p]}{\partial p}, \tag{7}$$

where Y is an outcome and $\hat{p}$ is a propensity score based on an instrument Z. That is, the estimated propensity score measures the extent of the program, and the MTE is the

[71] Policies to increase reskilling among workers with access to higher education include lowering commuting costs (e.g., building schools), increasing awareness (e.g., information campaigns), and providing financial support (e.g., reskilling benefits). We find that the MTE estimates are similar for different instrumental variables, suggesting that our conclusions are robust to the choice of policy instrument.

[72] Because primary school records are only available for the subsample of workers who graduated after 2002, we cannot estimate heterogeneous returns by workers' primary school grades.

change in the outcome generated by an expansion in the program. Heckman and Vytlacil (2005) show that all treatment parameters can be written as weighted averages of the MTE. For example, the LATE in Section 4 is simply the average MTE evaluated between the propensity scores of workers with and without access to higher education.

With a continuous instrument, obtaining a continuous distribution of propensity scores is straightforward. Because our access instrument Z is binary, however, we combine our instrument with continuous covariates X to trace out a distribution of propensity scores with continuous support. Kline and Walters (2016) and Walters (2018) follow similar strategies, combining an access instrument with continuous covariates to estimate marginal treatment effects.

Our strategy is to interact our access IV with workers' age and distance to education facilities to estimate the propensity scores:

$$p(D_i = 1) = \mu(X_i, Z_i) = \mu(\text{Age}_i, \text{Distance}_i, \text{Access}_i), \tag{8}$$

where D_i is an indicator for enrolling in a post-secondary degree within ten years after the accident. Proximity to schools is a common instrument in the literature on the returns to education,[73] and the inclusion of worker age is consistent with standard lifecycle models of human capital investment.[74] Intuitively, because direct access to higher education matters more for younger workers living closer to education facilities, these covariates allow us to identify the marginal effects of reskilling more workers. We show that our estimates are robust to using either distance or age as the interacting covariate.

To obtain the MTEs, we regress the outcome variable on the propensity score and

[73]See, e.g., Card (1993), Cameron and Taber (2004), Carneiro, Heckman, and Vytlacil (2011), and Mountjoy (2022). In contrast to these papers, our strategy based on the interaction with the access instrument allows us to separately control for workers' proximity to training facilities.

[74]Two factors could account for the variation in reskilling (more precisely, compliance with the access policy) based on age under the assumption of a shared MTE schedule. First, younger workers may reskill at a higher rate because they have more working years left to reap the annual returns to new skills. For example, McCall, Smith, and Wunsch (2016) present a lifecycle model of human capital investment in which skill-depreciation shocks can push workers back to school, with stronger responses for younger workers, all else equal. Second, older workers may find schooling more costly due to, e.g., personal preferences or lack of information. For example, Traiberman (2019) provides evidence that older workers have higher non-pecuniary costs of switching occupations, despite earning similar annual returns to such transitions.

separate controls for our covariates and calculate the MTE in a second step:

$$\mathbb{E}[Y_i] = g(\text{Age}_i, \text{Distance}_i) + f(\hat{p}_i) \tag{9}$$

$$\text{MTE}(p) = \frac{\partial f(p)}{\partial p}, \tag{10}$$

where $g(\cdot)$ and $f(\cdot)$ are flexible functions we specify in Section 5.1.1. As outcomes Y, we use annual earnings, public transfers, and tuition costs at different time horizons after injury, allowing us to compute the social, private, and public returns to reskilling. Hence, from a practical perspective, Equation (9) relates our reduced-form outcomes from Section 4 to workers' propensities to reskill (based on their access, commuting distances, and age), and the MTE in Equation (10) is the derivative of that relationship evaluated at a specific propensity score.

The identifying assumption in Equation (9) is that the schedule of MTEs on annual outcomes before retirement $f(\cdot)$ does not depend on workers' commuting distances to higher education or age. This exclusion restriction allows us to control for worker commuting distances and age separately (through $g(\cdot)$) and only use their interactions with our access instrument to trace out the MTE function. Again, we show robustness to estimating the MTEs based on either of the two interactions separately.[75]

5.1.1 Estimation

We estimate the propensity score and outcome equation for injured workers below age 50, who all have at least ten years left until retirement age. We use the IPW weights defined earlier to account for differences between workers with and without access to education.

[75] The robustness for different instrumental variables addresses concerns about the excludability of each instrument and also suggests that our MTEs are generalizable across policy instruments.

Propensity scores. We estimate the propensity scores using a flexible logit specification in worker age, distance to education facilities, and access to higher education:

$$p(D_i = 1) = \mu(\text{Age}_i, \text{Distance}_i, \text{Access}_i) \tag{11}$$

$$= \mu(g(\text{Age}_{ie}, \text{Distance}_{ie}) + \beta_1 \text{Access}_i \tag{12}$$

$$+ \beta_2 \text{Age}_i \times \text{Access}_i + \beta_3 \text{Age}_i^2 \times \text{Access}_i \tag{13}$$

$$+ \beta_4 \text{Distance}_i \times \text{Access}_i + \beta_5 \text{Distance}_i^2 \times \text{Access}_i)), \tag{14}$$

where $\mu(\cdot)$ is a logit link function, and $g(\cdot)$ includes a quadratic in age and commuting distance, and event-year fixed effects:

$$g(\text{Age}_i, \text{Distance}_i) = \pi_{0e} + \pi_1 \text{Age}_i + \pi_2 \text{Age}_i^2 + \pi_3 \text{Distance}_i + \pi_4 \text{Distance}_i^2$$

Table A.13 reports the propensity score estimation results, showing significant interaction terms between the access instrument and workers' age and distance to education facilities (F-stat of 15.3). Confirming standard theoretical predictions, the access policy matters more for younger workers living closer to education facilities.

Appendix Figure A.19.(a) provides a graphical representation of the first stage, showing that younger workers respond more strongly to the access policy (lines of best fit) and that commuting distances generate variation in reskilling among workers with the same age and eligibility for education (binned scatters around lines). Figure A.19.(b) plots the distribution of propensity scores by treatment status, showing continuous overlap from 0 to 0.5.

Outcome equation. We use a quadratic polynomial in the propensity score for the outcome equation, corresponding to a linear MTE function.[76] We estimate the effects for

[76] Cornelissen et al. (2018) also use a quadratic polynomial in the outcome equation.

different horizons k after injury:

$$Y_{it} = g_k(\text{Age}_{ie}, \text{Distance}_{ie}) + f_k(\hat{p}_{ie}) + \varepsilon_{it} \tag{15}$$

$$= g_k(\text{Age}_{ie}, \text{Distance}_{ie}) + \alpha_{1k}\hat{p}_{ie} + \frac{\alpha_{2k}}{2}\hat{p}_{ie}^2 + \varepsilon_{it} \tag{16}$$

$$\text{if} \quad t = e + k \quad \text{for} \quad k \in [0, 10], \tag{17}$$

where we control for age using the flexible specification $g(\cdot)$ in Equation (15). We calculate standard errors using a Bayesian bootstrap (Shao and Tu (2012)) over the propensity score and outcome equations (12)-(14) and (16).

Appendix Tables A.14-A.17 report the estimation results for the outcome variables that capture the benefits and costs for workers, government, and society.

5.2 Marginal Returns

We use the marginal treatment effects to calculate the present-discounted incomes generated by reskilling workers of age a from a rate of p. In particular, let I denote a measure of annual net income (benefits minus costs), the present-discounted marginal return is:

$$\text{MR}(a, p) = \sum_{k=0}^{\bar{A}-a} \beta^k \left(\alpha_{1k}^I + \alpha_{2k}^I p\right), \tag{18}$$

where α_k^I are the marginal treatment effects estimated in Equation (16) and β is a discount factor. As in Section 4.4, we assume treatment effects are constant after year $k = 10$ and until retirement age $\bar{A}$.

Figure 9 depicts the marginal social, private, and public returns (corresponding to the Total, Workers, and Government rows in Table 5) on reskilling for different age cohorts. To read the figure, consider a policy that induces 16.5% of workers aged 40 to reskill (from a baseline rate of 2.5%), which is close to the current program. A marginal expansion of the program for these workers generates a monetary surplus of \$350,000, which is split into \$80,000 for workers and \$270,000 for the government. Reassuringly, the levels of returns align with the cost-benefit estimates for compliers in Table 5.[77]

[77]Following Heckman and Vytlacil (2005), the LATE estimates in Table 5 correspond to the mid-

More generally, Figure 9 shows that the marginal returns on reskilling are decreasing in worker age (between-cohort effect) and the share of each age cohort induced to reskill (within-cohort effect). The within-cohort effect captures that workers with higher returns to reskilling are less resistant to the programs. The between-cohort effect stems from older workers having fewer working years left.

While Panel (c) reflects the surplus on the government budget, Panel (b) only corresponds to private surpluses if workers have linear utility of income and derive no non-monetary benefits from reskilling. As Appendix E.1 shows, the omission of mental health aspects likely understates the benefits of reskilling in shielding injured workers from depression.

[Figure 9 around here]

Appendix Figure A.20 reports confidence bands for the marginal returns curves calculated using a Bayesian bootstrap. As the figure shows, the confidence bands of the policy counterfactuals are relatively wide, especially for the private returns analyses. Hence, to further assess the robustness of our marginal returns analysis, Figure A.21 repeats the MTE estimation, focusing on either workers' age or distances to training facilities as the interacting covariate in the propensity score equations (12)-(14). The marginal return estimates across specifications are very similar and not significantly different. Reassuringly, the optimal rates of reskilling (that set the marginal returns to zero) presented in Section 5.3 are robust to the choice of interacting covariates in the MTE estimation.

5.3 Optimal Policy

In Figure 10, we calculate the rates of reskilling that maximize the social, private, and public returns for each worker age. Figure 11 shows the total returns attained by each of the policies. A comparison to the current rates of reskilling reveals three insights.

points on the marginal return curves (Figure 9) between the reskilling rates of the workers with and without access to higher education. Brinch, Mogstad, and Wiswall (2017, Figure 1) provide a geometric representation of the relationship between the LATE and a linear MTE curve.

First, the current reskilling rates are substantially below the social optimum. Averaging across age cohorts, the optimal and current rates of reskilling are 33% and 12%, respectively. The current rates capture 60% of the potential social returns, leaving an unrealized return of $30,000 per injured worker.

Second, the current rates of reskilling are especially sub-optimal for workers in the middle of their careers (age 40 to 50). In particular, the current rates realize only 35% of the potential monetary surplus for middle-aged workers, implying a missed surplus of $50,000 per injured worker in this age category. By contrast, the reskilling rates among the youngest and oldest workers (age 20-30 and 55-65, respectively) are close to the social optimum.

Third, reskilling rates among middle-aged workers appear sub-optimal for both the government and workers. In particular, government subsidies for reskilling (covering tuition and benefits) pay for themselves for about 34% of middle-aged workers. From the viewpoint of middle-aged workers, a reskilling share of around 39% would maximize their present-discounted lifetime income. The fact that only 6% of these workers opt into the program points to substantial barriers to reskilling for this group of workers. In particular, the marginal middle-aged worker currently leaves $75,000 of private return on the table by not reskilling (Figure 9.(b)).

[Figures 10 and 11 around here]

What could explain the lack of reskilling among middle-aged workers? Our previous analysis shed light on the roles of access to education,[78] commuting costs,[79] financial considerations,[80] and mental health.[81] To complement this quantitative evidence, we con-

[78]Section 4.1.4 shows that access to education is critical for injured workers to reskill. Yet, Figure 10 shows that underinvestment occurs even among workers with direct eligibility for higher education.

[79]Table A.13 shows that commuting time to educational facilities is an important determinant for reskilling. For example, lowering commuting times by an hour increases reskilling rates by three percentage points for the average injured worker.

[80]Section 4.4 shows that reskilling benefits provide substantial financial support for workers, which may be particularly important for older workers with higher living expenses.

[81]Appendix E.1 shows that omitting mental health considerations likely understates the benefits of reskilling, thus exacerbating the puzzle of why more injured workers do not reskill.

ducted qualitative interviews of student counselors, caseworkers, and industry experts.[82] The interviews pointed to a lack of awareness of educational opportunities as a critical reason why older workers do not reskill. By contrast, the MTE framework rationalizes the lack of reskilling with a worker-specific *resistance* or *distaste* for treatment (Cornelissen et al. (2016)). For example, if the psychic costs of reskilling increase with age, that could explain why middle-aged workers do not invest in human capital. By this view, Figure 9.(b) quantifies how high the psychic costs of reskilling must be to rationalize why injured workers do not reskill.

5.3.1 General Equilibrium Effects

A takeaway from Figures 10 and 11 is that reskilling programs may be expanded for injured workers. Yet, large increases in reskilling could have general equilibrium effects, for example, by bidding down wages (Heckman, Lochner, and Taber (1998)). In Appendix F, we incorporate such equilibrium effects by embedding our estimated treatment effects into a calibrated model of the labor market. Our calibration shows that the optimal reskilling rates are robust to labor market equilibrium effects, which partly reflects that injured workers constitute a minor share of aggregate labor supply.

6 Conclusion

This paper provides the first evidence on how workers invest in human capital after losing physical abilities and how these investments allow workers to transition into more cognitive occupations.

Our analysis delivers three takeaways. First, the transition of workers from physical to cognitive jobs requires ambitious investments in human capital, lasting multiple years at the higher education level. Second, higher education of injured workers yields large returns, especially for the government, by saving on disability benefits. Finally, current

[82]We thank Peter Aaskov (student counselor at the Construction Architect program), Laila Nielsen and Lilian Hinsch (directors of the rehabilitation team at Varde Municipality), and Annette Juul Jensen (senior consultant at CABI) for helpful insights about the barriers to reskilling for injured workers.

rates of reskilling are substantially below the social optimum, especially for mid-aged workers. Our analysis shows that reskilling older workers is both possible and highly favorable after adverse career shocks, as affected workers may otherwise end up on public assistance.

Our findings suggest that policymakers may want to expand the access of displaced manual workers to higher education. For example, policies that work to remove obstacles for disabled workers to enroll in further education may include financial support and the provision of direct access for workers with vocational degrees to enter higher education. These policies may also alleviate other displacement shocks to manual occupations, such as automation or globalization.

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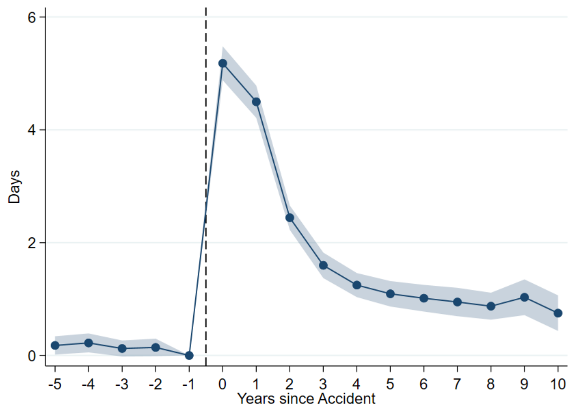
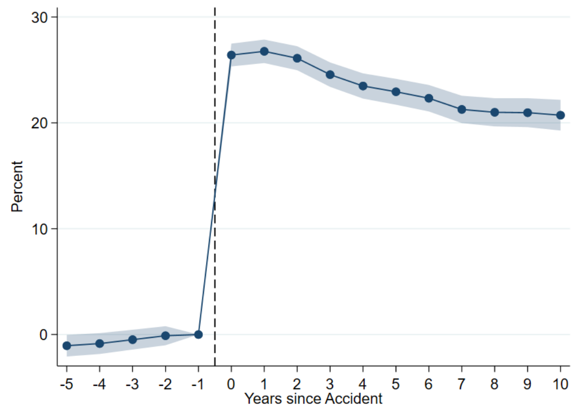
Main Figures

Figure 1: Worker Outcomes around Accident

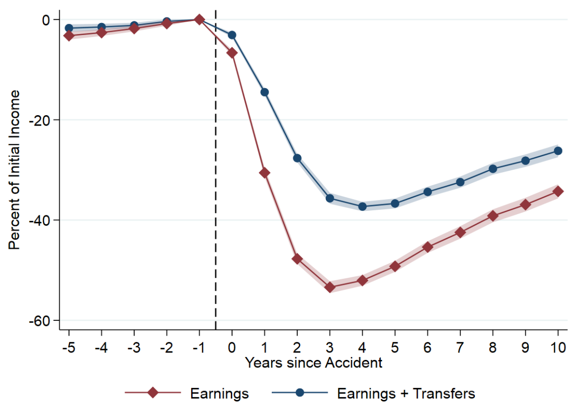
(a) Days in Hospital



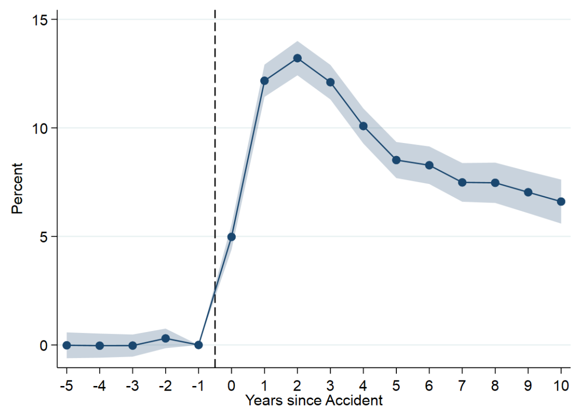
(b) Pain-Killer Prescription



(c) Income



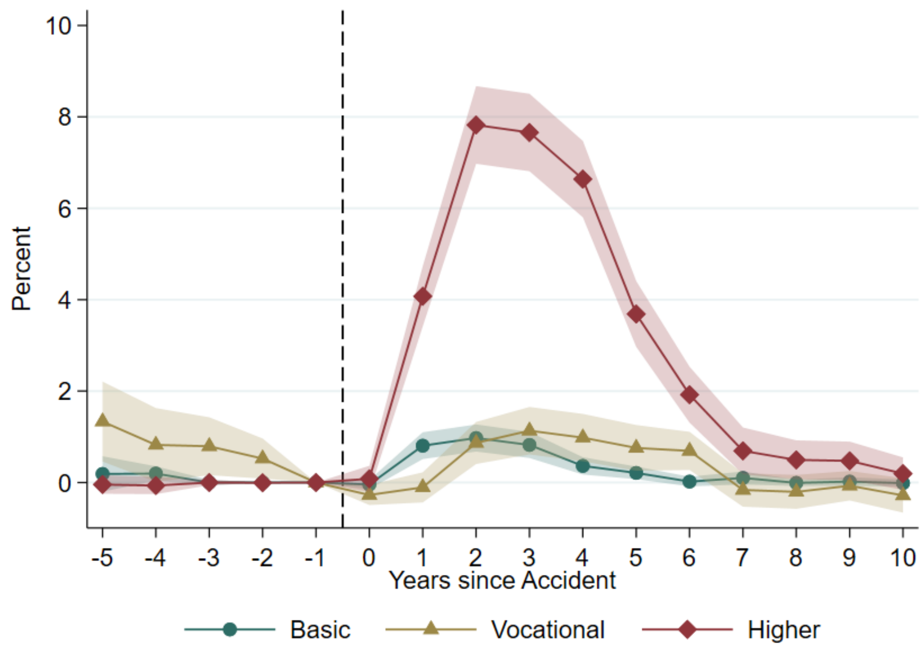
(d) Antidepressant Prescription



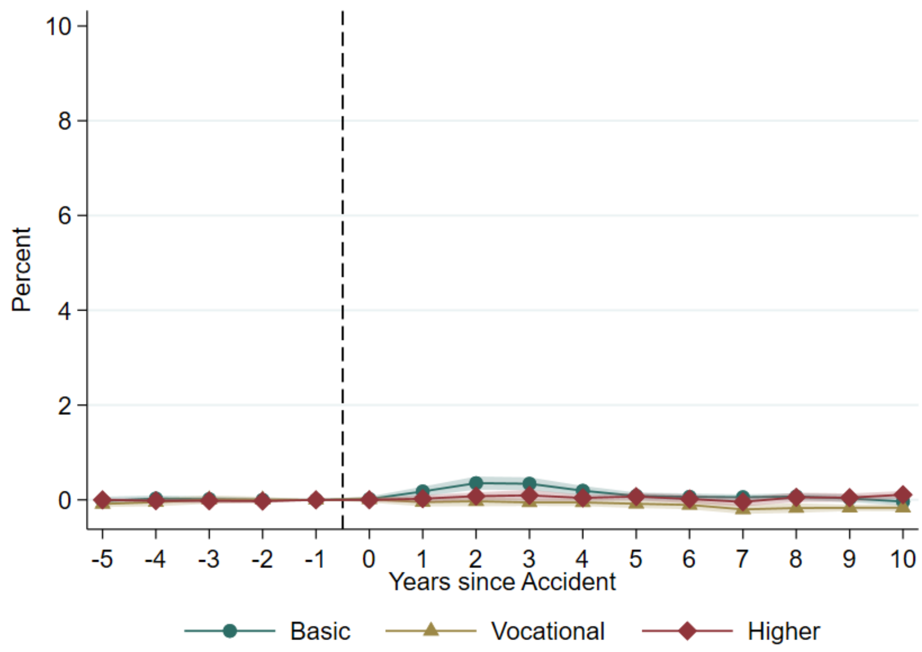
Notes: This figure shows the differences-in-differences in outcomes (measured relative to year -1) between the "Injury" and "Match" workers from Table 2. Shaded areas represent 95% confidence bands, estimated using the regression equation (1). Panel (a) shows the days spent in the hospital, Panel (b) shows the share of workers with a prescription for pain-relieving medications, Panel (c) shows the labor income measured in percent of the average level in year -1, and Panel (d) shows the share of workers with a prescription for antidepressant medications.

Figure 2: Participation in Courses around Accident

(a) Degree

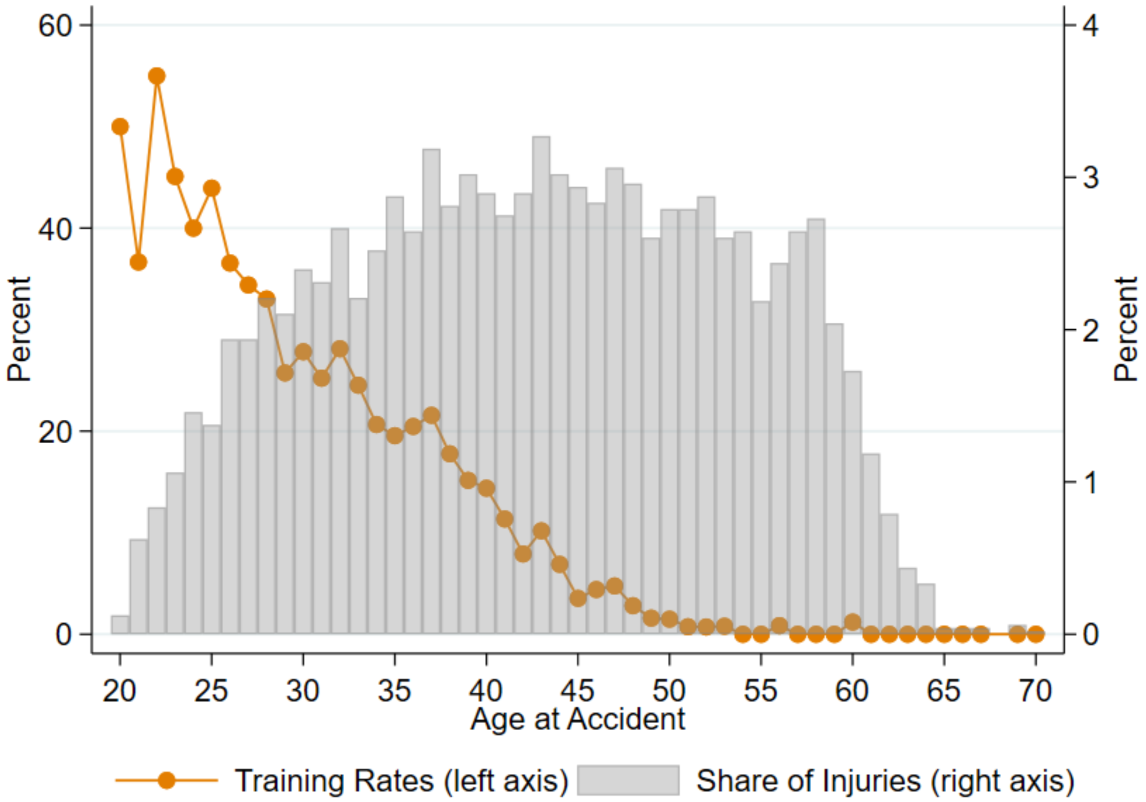


(b) Non-Degree



Notes: This figure shows participation (measured in full-time equivalents) in degree and non-degree courses by level of education. *Basic* is primary and high school (academic track), and *Higher* is all post-secondary education. This figure focuses on workers who, before the work accident, had a secondary or vocational degree that gives access to higher education. The graphs show differences-in-differences in outcomes between the "Injury" and "Match" workers from Table 2, indexed to year -1. Shaded areas represent 95% confidence bands estimated using the regression equation (1).

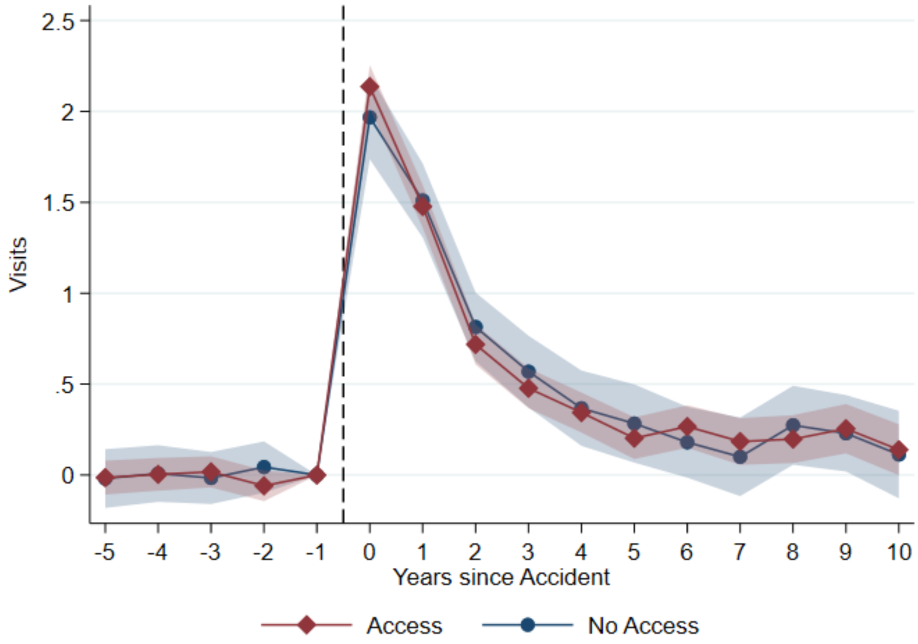
Figure 3: Enrollment in Higher Degrees after Work Accident by Worker Age at Accident



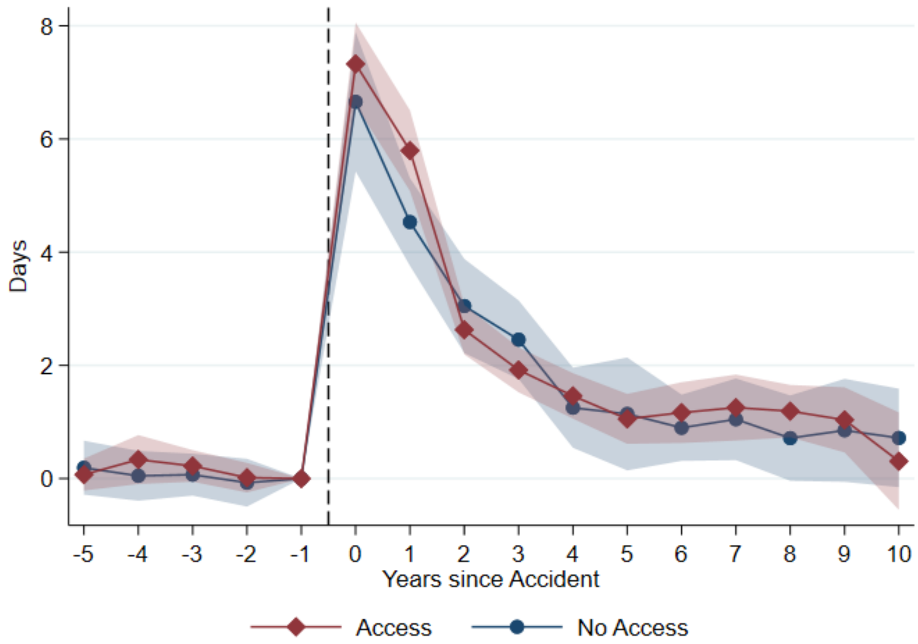
Notes: The line shows the enrollment of workers in higher degrees (measured within six years after a work accident) according to each worker's age at the time of the accident. The histogram shows the distribution of work accidents by each worker's age at the the time of the accident. The figure focuses on workers who, before the work accident, had a secondary or vocational degree that gives access to higher education.

Figure 4: Hospitalization around Accident

(a) Number of Hospital Visits



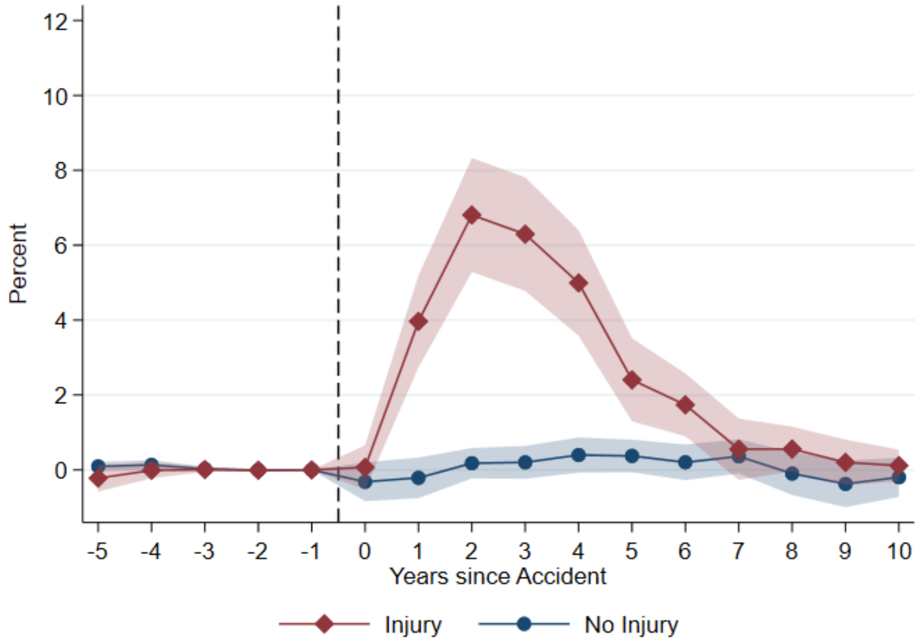
(b) Days in Hospital



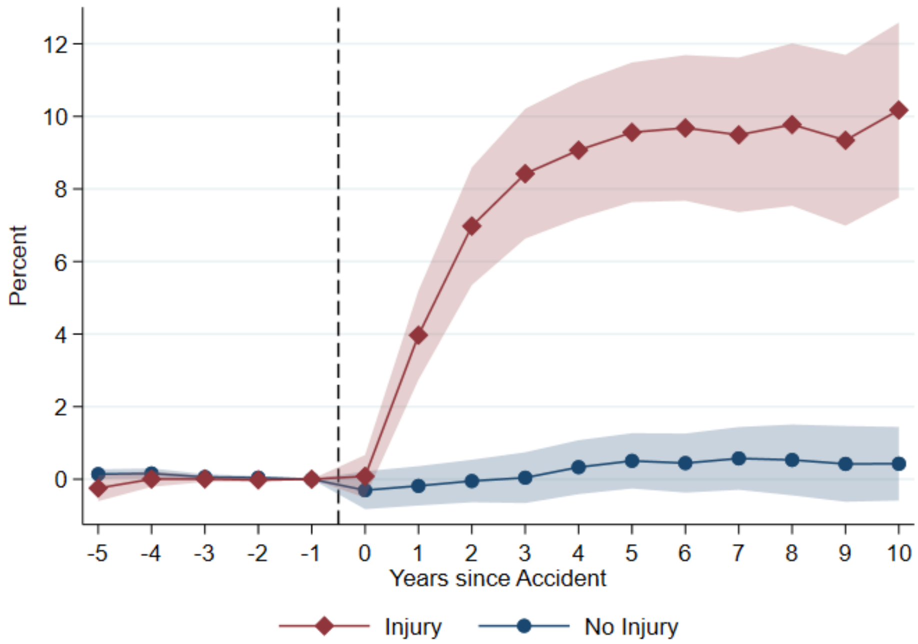
Notes: This figure shows the hospitalization of workers, split by whether the workers have access to higher education upon injury. The groups correspond to the "Access" and "No Access, IPW" columns of Table 3. The graphs show differences-in-differences in outcomes between the "Injury" and "Match" workers from Table 2, indexed to year -1. This figure focuses on workers with a vocational degree within craft work. Shaded areas represent 95% confidence bands, estimated using the regression equation (1).

Figure 5: Pursuit of Higher Degrees ("Access" − "No Access")

(a) Participation (Flow)



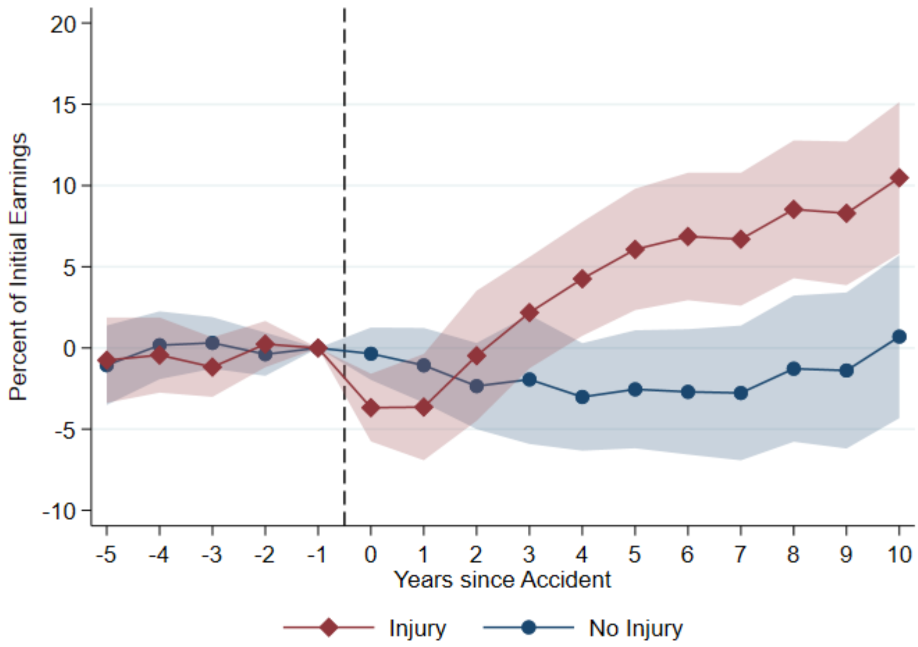
(b) Participated (Stock)



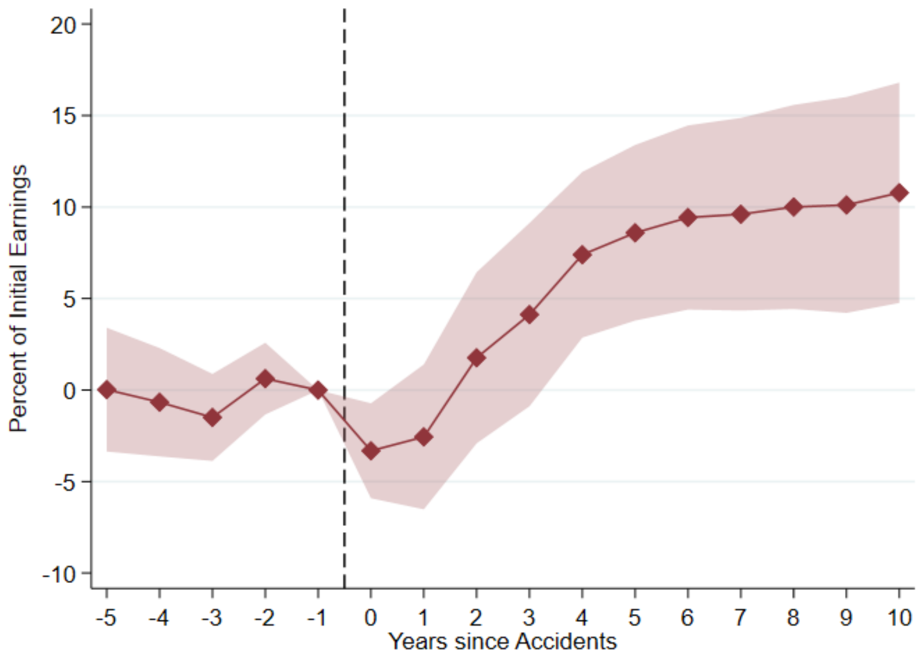
Notes: This figure shows the differences in the pursuit of higher degrees according to workers' access to higher education. The figure focuses on craft workers. Panel (a) shows enrollment in the given year, and Panel (b) shows the accumulated enrollment. The plots are differences-in-differences between the "Access" and "No Access, IPW" workers from Table 3, indexed to year -1. Shaded areas represent 95% confidence bands, estimated using Equation (2).

Figure 6: Labor Earnings around Work Accident

(a) "Access" – "No Access"

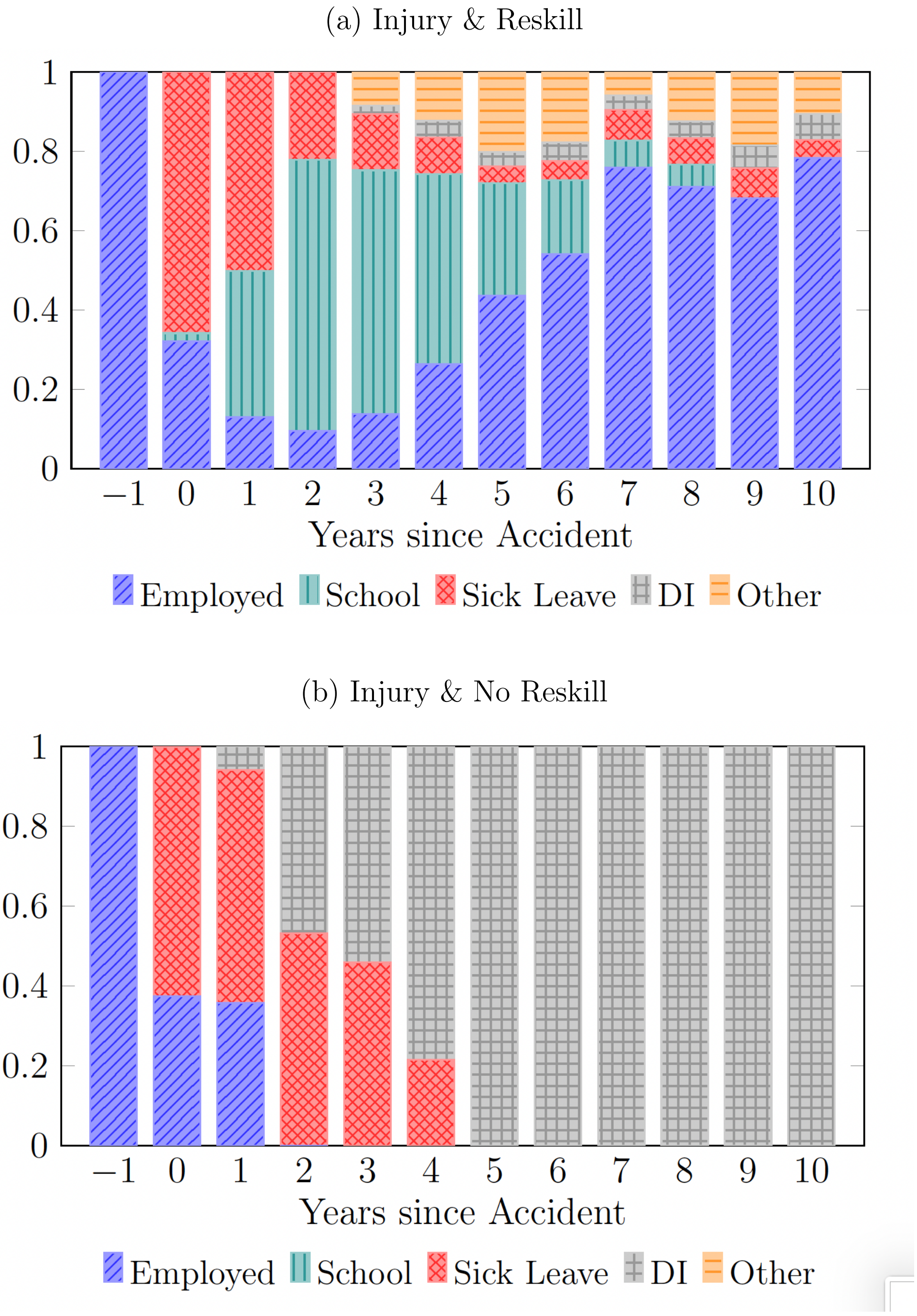


(b) Triple Difference



Notes: This figure shows the differences in labor earnings of workers according to their access to higher education. Labor earnings are measured in percent of workers' average earnings in year -1. The figure focuses on craft workers. Panel (a) shows the difference-in-differences in outcomes between the "Access" and "No Access, IPW" workers from Table 3, estimated using Equation (2). Panel (b) shows the difference between the two differences-in-differences (a "triple difference" estimator). Shaded areas represent 95% confidence bands.

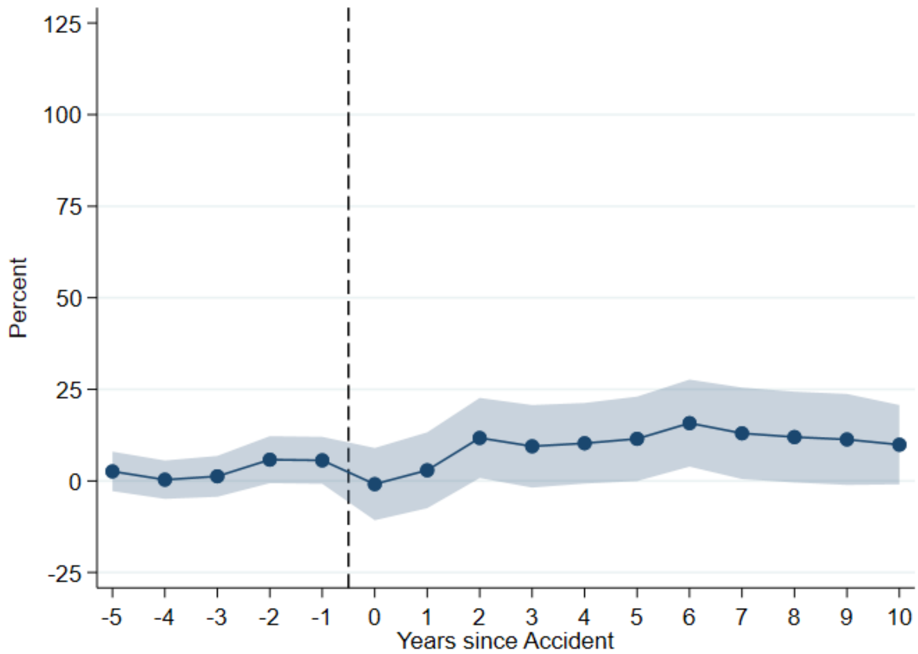
Figure 7: Labor Supply



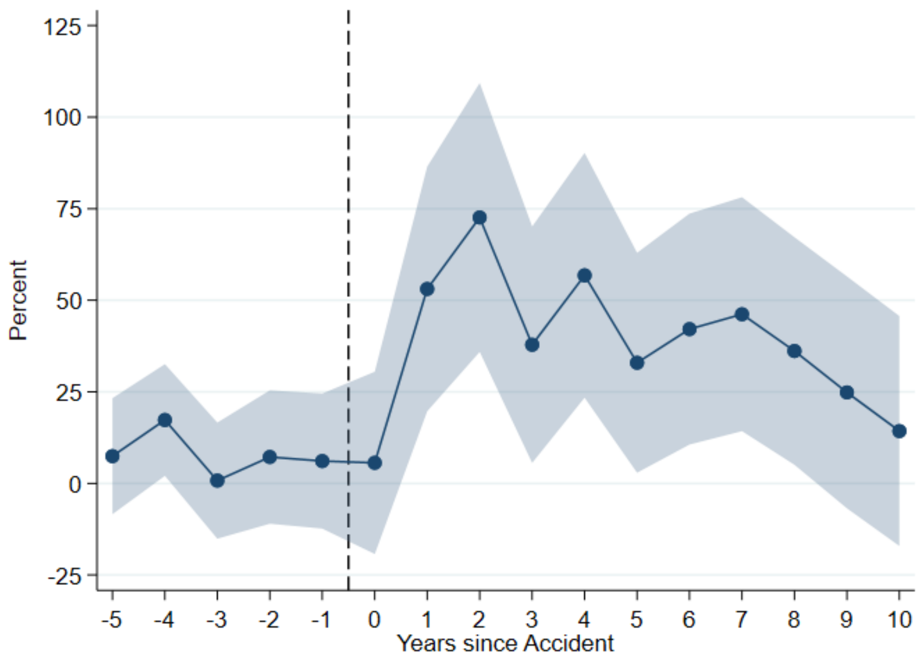
Notes: This figure shows the labor supply of complier workers who comply with access to higher education by pursuing a higher degree after work accidents. *Employed* is fulltime employment. *School* is enrollment in a higher degree. *Sick Leave* refers to receiving sickness benefits. *DI* is disability insurance. *Other* is mainly unemployment and non-participation. Panels (a) and (b) report treated and control complier means, estimated using Equations (3)-(5).

Figure 8: Antidepressant Prescription

(a) Injury & Reskill



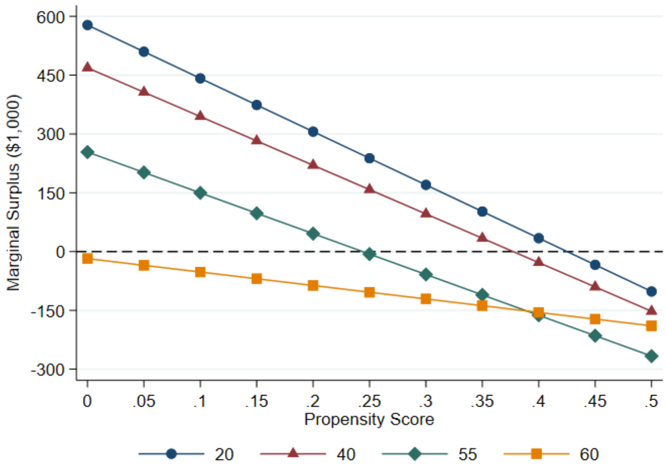
(b) Injury & No Reskill



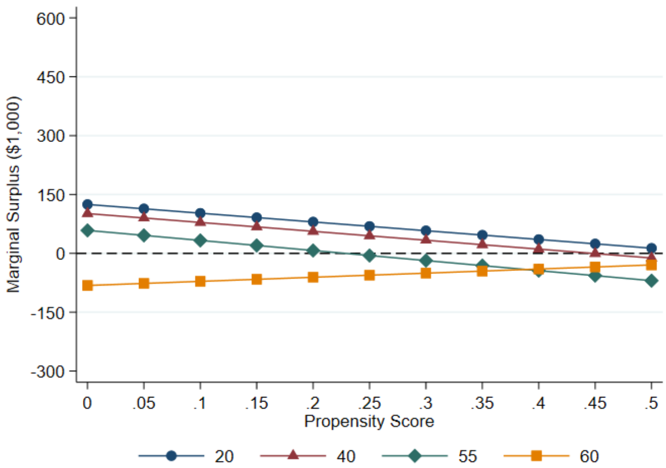
Notes: This figure shows the prescriptions of antidepressants for workers who comply with access to higher education by pursuing a higher degree after work accidents. Panels (a) and (b) report treated and control complier means, estimated using Equations (3)-(5).

Figure 9: Marginal Returns on Reskilling Workers of Different Ages ($1,000)

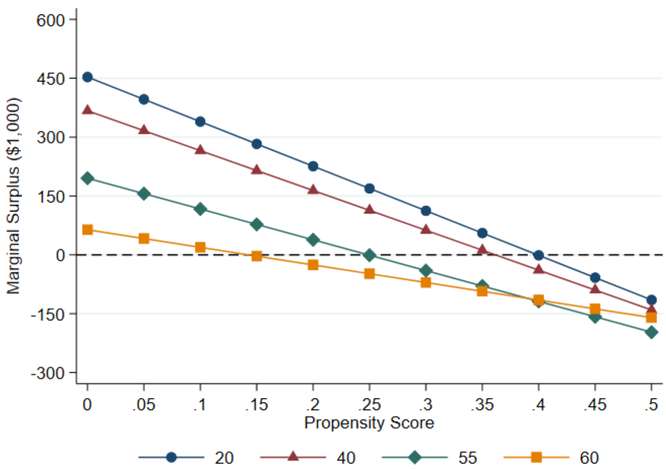
(a) Total (Social Returns)



(b) Workers (Private Returns)

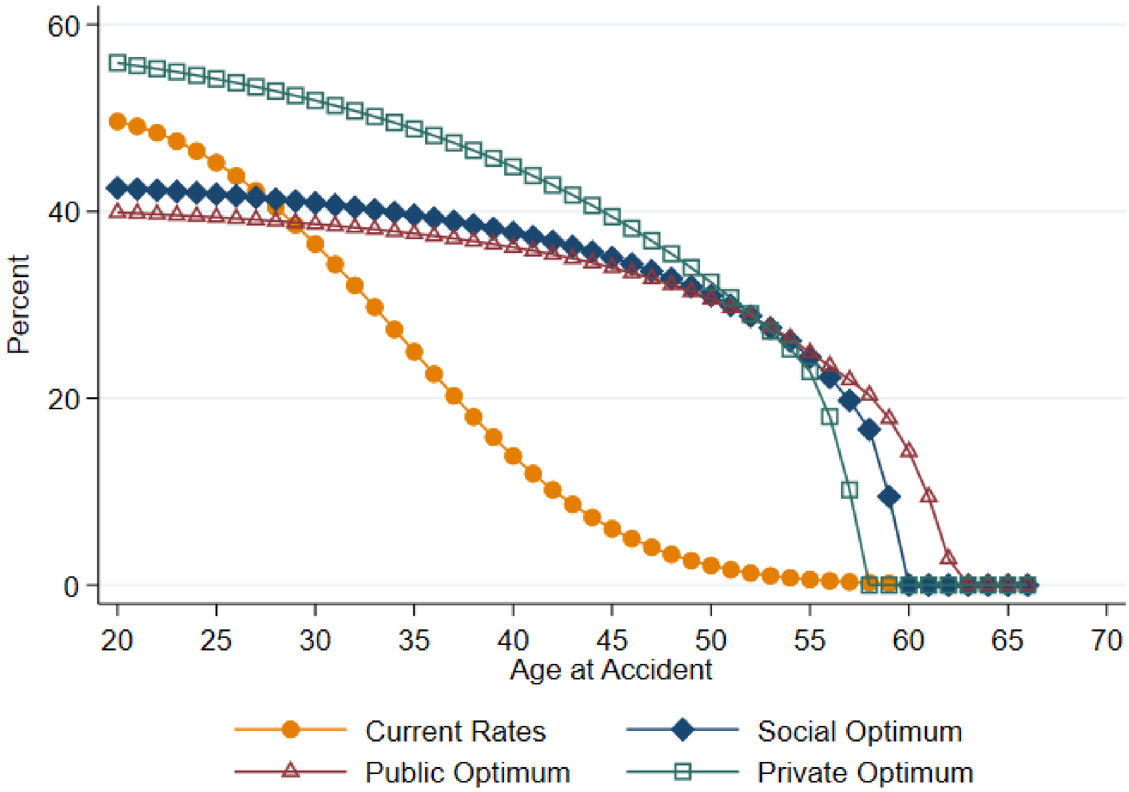


(c) Government (Public Returns)



Notes: This figure shows the marginal returns of reskilling workers of different ages (Equation (18)). Social returns (Panel (a)) is the sum of returns for workers (Panel (b)) and the government (Panel (c)), each defined as in Table 5.

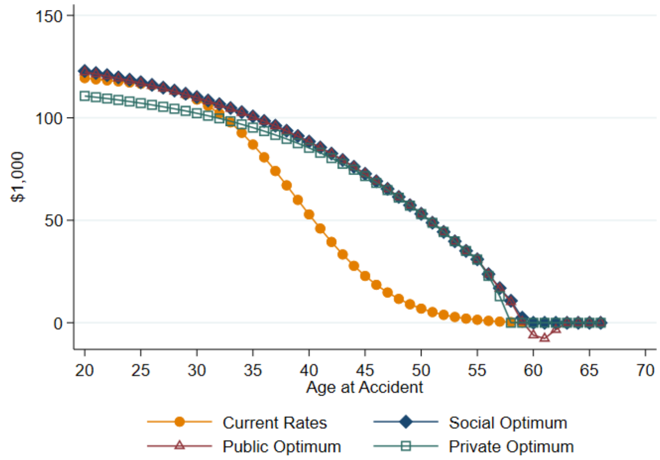
Figure 10: Optimal vs. Current Rates of Reskilling



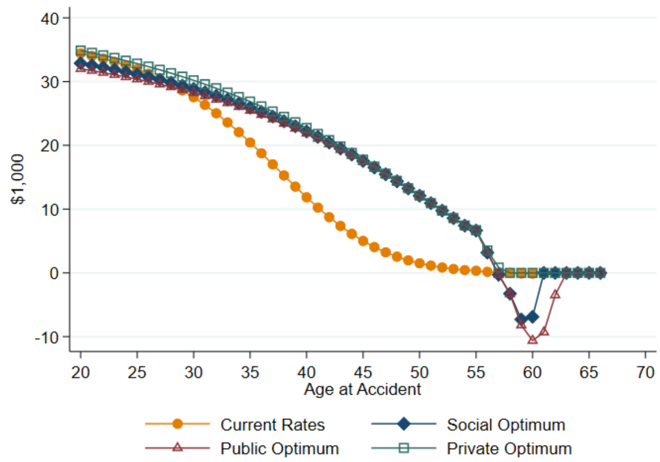
Notes: This figure compares the current rates of reskilling across worker ages with the optimal rates from the perspective of society (social optimum), injured workers (private optimum), and the government (public optimum). The optimal rates maximize the returns from Figure 9 (Panels (a), (b), and (c), respectively).

Figure 11: Returns on Reskilling Policies ($1,000 Per Injured Worker)

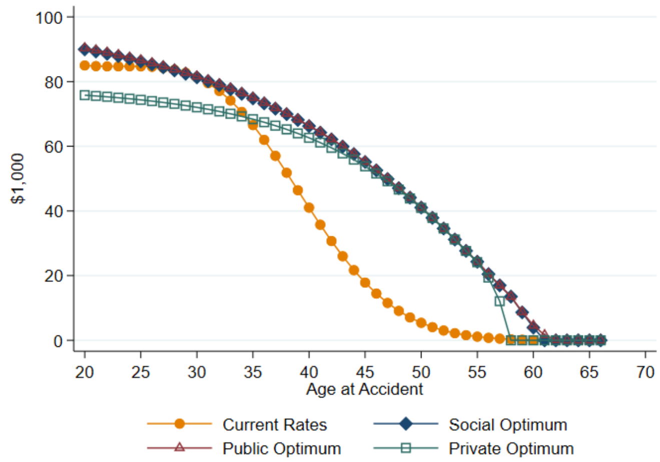
(a) Total (Social Returns)



(b) Workers (Private Returns)



(c) Government (Public Returns)



Notes: This figure shows the total returns of reskilling policies. Social returns (Panel (a)) is the sum of returns for workers (Panel (b)) and the government (Panel (c)), each defined as in Table 5.

Main Tables

Table 1: Occupations with the Highest Accident Rates

Occupation	Injuries/ 1000 FTEs	Most Common Injury	
		Event	Body Part
Carpenters	15.54	Fall Injury	Back, incl. spine
Elementary workers, n.e.c.	15.51	Fall Injury	Back, incl. spine
Joiners and carpenters, n.e.c.	15.08	Fall Injury	Back, incl. spine
Heavy truck and lorry drivers	13.47	Fall Injury	Back, incl. spine
Plumbers and pipe fitters	13.43	Fall Injury	Back, incl. spine

Notes: This table shows the five occupations (employing at least 10,000 full-time equivalents) with the highest rate of work accidents between 1996 and 2017. The table only includes accepted claims. The "Most Common Injury" columns report characteristics of the most common injuries that caused loss of earning capacity.

Table 2: Worker Outcomes before Accident

	Injury	No Injury		Std. Diff.
		Random	Match	Injury - Match
Outcomes in Year -1				
Demographics				
Age	43.32	43.11	43.32	0.0%
	(10.14)	(10.89)	(10.14)	
Female (%)	39.16	45.22	39.16	0.0%
	(48.81)	(49.77)	(48.81)	
Cohabiting (%)	70.62	72.70	71.74	-2.5%
	(45.55)	(44.55)	(45.03)	
School-aged Children (%)	33.47	31.68	32.17	2.8%
	(47.19)	(46.53)	(46.72)	
Property Owner (%)	58.57	64.94	61.63	-6.2%
	(49.26)	(47.72)	(48.63)	
Education				
Years of Schooling	12.85	14.12	12.91	-2.3%
	(2.63)	(2.55)	(2.56)	
Primary (%)	31.54	17.64	31.54	0.0%
	(46.47)	(38.12)	(46.47)	
Vocational (%)	51.18	42.14	51.18	0.0%
	(49.99)	(49.38)	(49.99)	
High School (%)	1.60	4.92	1.60	0.0%
	(0.01)	(0.02)	(0.01)	
Post-Secondary (%)	15.68	35.30	15.68	0.0%
	(36.36)	(47.79)	(36.36)	
Employment				
Hours Worked (Yearly)	1,691.64	1,735.67	1,724.33	-4.5%
	(551.49)	(430.04)	(862.41)	
Labor Income (1000 DKK)	377.40	438.53	380.96	-2.6%
	(126.45)	(294.46)	(142.02)	
Hourly Wage	235.01	294.68	227.82	4.8%
	(172.02)	(808.44)	(126.48)	
Job Tenure (Years)	3.62	4.74	4.02	-12.0%
	(3.22)	(4.15)	(3.45)	
Labor Market Experience (Years)	19.53	20.44	20.76	-13.2%
	(9.33)	(10.24)	(9.37)	
Public Sector (%)	30.07	25.91	30.07	0.0%
	(45.86)	(43.82)	(45.86)	
Union Membership (%)	91.11	81.07	89.77	4.6%
	(28.46)	(39.18)	(30.31)	
Wealth				
Debt-to-Income Ratio	28.49	26.94	23.71	18.1%
	(27.35)	(31.85)	(25.44)	
Savings-to-Income Ratio	14.02	22.93	16.31	-9.3%
	(23.64)	(37.94)	(25.43)	
Occupation				
Physical Ability Requirement (Std.)	0.75	-0.07	0.71	3.7%
	(0.93)	(1.11)	(0.92)	
Cognitive Ability Requirement (Std.)	-0.39	0.11	-0.37	-3.1%
	(0.84)	(0.95)	(0.86)	
Injury Rate (x 1000)	10.35	6.06	10.08	5.4%
	(5.03)	(4.86)	(4.94)	
Reskilling				
Access to Higher Education (%)	48.82	58.70	48.82	0.0%
	(49.99)	(49.24)	(49.99)	
Travel Time to Higher Education (Min.)	34.08	32.83	33.49	2.4%
	(24.29)	(26.41)	(24.84)	
Injury				
Earnings Capacity Loss (%)	36.58	0.00	0.00	-
	(22.20)	(0.00)	(0.00)	
Personal Impairment (%)	12.44	0.00	0.00	-
	(10.03)	(0.00)	(0.00)	
Year of Injury	2,004.92	2,006.73	2,004.92	0.0%
	(4.84)	(5.60)	(4.84)	
Observations	14,481	14,481	14,481	

Notes: The "Injury" column shows the average outcomes of workers in the year before a work accident. Standard deviations are reported in parentheses. The "No Injury" columns show workers who satisfy the pre-event employment requirements but do not experience work accident in the event year. The "Random" subcolumn shows averages for randomly chosen workers (one-to-one). The "Match" subcolumn shows averages for workers with the age, gender, education level, occupation, and industry as the "Injury" workers in the year before the injury (one-to-one random match within cells). The "Std. Mean Diff" column shows the standardized mean difference between the "Injury" and "Match" workers, where absolute values above 25% is a standard threshold for assessing imbalance (Stuart and Rubin (2008)). See Table A.1 for definitions of the outcome variables.

Table 3: Worker Outcomes before Accident

	Access	No Access Raw	No Access IPW	Std. Diff. Access - IPW
Outcomes in Year -1				
Demographics				
Age	41.83	43.37	42.35	-5.0%
	(10.78)	(9.74)	(10.04)	
Female (%)	19.40	55.13	24.10	-15.9%
	(23.39)	(49.74)	(34.59)	
Cohabiting (%)	73.18	70.32	71.09	4.7%
	(44.28)	(45.69)	(45.32)	
School-aged Children (%)	31.26	36.11	34.42	-6.7%
	(46.33)	(48.04)	(47.50)	
Property Owner (%)	66.86	53.02	61.55	11.2%
	(46.35)	(49.92)	(48.43)	
Education				
Years of Schooling	14.26	13.35	14.19	16.0%
	(0.21)	(1.10)	(0.59)	
Primary (%)	0.00	0.00	0.00	0.0%
	(0.00)	(0.00)	(0.00)	
Vocational (%)	100.00	100.00	100.00	0.0%
	(0.00)	(0.00)	(0.00)	
High School (%)	0.00	0.00	0.00	0.0%
	(0.00)	(0.00)	(0.00)	
Post-Secondary (%)	0.00	0.00	0.00	0.0%
	(0.00)	(0.00)	(0.00)	
Employment				
Hours Worked (Yearly)	1,673.35	1,696.92	1,685.52	-2.2%
	(593.34)	(508.56)	(492.16)	
Labor Income (1000 DKK)	387.44	359.39	389.44	-1.6%
	(120.89)	(122.11)	(124.77)	
Hourly Wage (DKK)	246.97	220.37	241.39	3.0%
	(217.09)	(0.00)	(141.25)	
Job Tenure (Years)	3.88	3.47	3.95	-2.0%
	(3.36)	(3.13)	(3.35)	
Labor Market Experience (Years)	20.35	18.58	19.85	5.4%
	(9.31)	(8.98)	(9.22)	
Public Sector (%)	20.38	46.73	23.20	-8.4%
	(31.33)	(49.90)	(36.03)	
Sick Leave (% of weeks)	4.51	4.71	4.35	1.4%
	(11.15)	(12.17)	(11.52)	
Union Membership (%)	90.83	91.84	92.01	-4.2%
	(28.79)	(27.38)	(27.09)	
Wealth				
Debt-to-Income Ratio (%)	32.80	33.39	33.29	-1.5%
	(32.07)	(32.67)	(32.44)	
Savings-to-Income Ratio (%)	14.65	13.13	13.10	6.7%
	(24.08)	(22.24)	(21.89)	
Occupation				
Physical Ability Requirement (Std.)	0.98	0.83	0.74	28.9%
	(0.83)	(1.02)	(0.82)	
Cognitive Ability Requirement (Std.)	-0.41	-0.47	-0.52	16.1%
	(0.71)	(0.66)	(0.72)	
Injury Rate (x 1000)	11.06	9.99	10.39	13.7%
	(4.64)	(4.58)	(4.98)	
Reskilling				
Access to Higher Education (%)	100.00	0.00	0.00	-
	(0.00)	(0.00)	(0.00)	
Travel Time to Higher Education (Min.)	35.40	31.02	33.32	8.6%
	(24.62)	(24.13)	(23.52)	
Injury				
Earnings Capacity Loss (%)	34.31	35.65	36.13	-8.2%
	(22.11)	(22.19)	(22.02)	
Personal Impairment (%)	12.82	12.09	12.88	-0.6%
	(11.01)	(9.21)	(10.64)	
Year of Injury	2,005.27	2,004.81	2,005.49	-4.6%
	(4.83)	(4.69)	(4.82)	
Observations	4568	2844	2844	

Notes: This table shows the characteristics of workers in the year before work accidents. Standard deviations are in parentheses. The “Access” column shows workers eligible for a higher degree (but have not attained one). The “No Access” columns show workers ineligible for a higher degree. The “IPW” column implements an Inverse Probability Weighing (IPW) of the workers according to a logistic regression of access to higher degrees on the covariates reported in this table. Appendix C details the IPW procedure. The “Std. Mean Diff” column shows the standardized mean difference between the “Access” and “IPW” workers, where absolute values above 25% is a standard threshold for assessing imbalance (Stuart and Rubin (2008)). See Table A.1 for definitions of the outcome variables.

Table 4: Job Characteristics (Injury & Reskill)

	Standard deviations from Economy Average		Change in Percent
	Year -1	Year +10	Year -1 to +10
	Injury + Reskill		
Physical Ability Requirements	1.670	-0.261	
	(0.265)	(0.311)	
Cognitive Ability Requirements	-0.002	0.710	
	(0.207)	(0.320)	
Earnings	-0.181	0.384	25.3
	(0.190)	(0.217)	(9.7)
Occupational Earnings Premium	-0.240	1.433	76.8
	(0.089)	(0.313)	(14.4)

Notes: This table shows the job characteristics of complier workers who are employed ten years after a work accident if they reskill. *Physical Ability* is defined as the average importance of Static Strength, Explosive Strength, Dynamic Strength, Trunk Strength, and Stamina, as measured by O*NET. *Cognitive Ability* is defined as the average importance of Fluency of Ideas, Originality, Problem Sensitivity, Deductive Reasoning, Inductive Reasoning, Information Ordering, Category Pleribility, Mathematical Reasoning, and Number Facility, as measured by O*NET. We calculate "Occupational Earnings Premium" as the average labor market earnings within each "Match" (Year-Occupation-Industry-Education-Age-Gender) cell in the full population of non-injured workers with at least three years full-time work leading up to year -1. Columns 1 and 2 are measured in standard deviations from the average occupational earnings premium of the "No Injury" workers matched on calendar year in Table A.3 (Column (1)). Column 3 reports the percent change in the worker's outcome. See Table A.1 for definitions of the outcome variables.

Table 5: Costs and Benefits of Higher Education for Injured Workers

	Per Retrained Worker ($)	Per Dollar of Education	Percent of Total
Workers	**200,216**	**2.9**	**41.9**
Earnings	343,718	4.9	72.0
Transfers	-182,614	-2.6	-38.2
Educ. Transfers	39,112	0.6	8.2
Government	**277,419**	**4.0**	**58.1**
Educ. Transfers + Tuition	-70,201	-1.0	-14.7
Transfers	182,614	2.6	38.2
Taxes	165,007	2.4	34.5
Total	**477,635**	**6.8**	**100.0**

Notes: This table shows the present discounted values of providing a higher degree for an injured worker of age 32, the average among the instrument compliers. *Earnings* are labor earnings after tax, *Transfers* include disability benefits, unemployment benefits, sickness benefits, and cash assistance, *Educ. Transfers* include reskilling benefits and State Education Support (SU), *Educ. Transfers + Tuition* expenses include tuition and education transfers, and *Taxes* refer to labor income taxes. Appendix E details our approach to the cost-benefit calculations.

Appendix (For Online Publication)

A Appendix Figures and Tables

A.1 Tables

Table A.1: Variable Definitions

	Variable	Definition
From Balancing Tables:		
Demographics		
(1)	Age	Age by 31st of December.
(2)	Female	Dummy indicating the individual is registered as female.
(3)	Cohabiting	Dummy indicating married couples and couples co-habiting at the same address.
(4)	School-aged Children	Dummy indicating children aged 6-16 cohabiting with the parent.
(5)	Property Owner	Dummy indicating that the public cash valuation of property owned by the individual exceeds 0 DKK.
Education		
(6)	Years of Schooling	Prescribed years of study associated with highest completed degree counting from grade 1.
(7)	Primary	Dummy indicating pre-school educations, primary education, preparatory courses, or Danish language courses at language centers as highest completed degree.
(8)	Vocational	Dummy indicating Vocational Education and Training (VET), qualifying educational programmes, or labor market educations (AMU) as highest completed degree.
(9)	High School	Dummy indicating upper secondary education as highest completed degree.
(10)	Post-Secondary	Dummy indicating short cycle higher education, vocational bachelors educations, bachelors-, masters-, or PhD programmes as highest completed degree.
Employment		
(11)	Hours Worked	From 2008-2017: Yearly number of payed hours. From 1995-2007: Yearly labor income (12) divided by hourly wage rates (13).
(12)	Labor Income	Total labor market income, including bonuses, amenities, wages payed under sick- and parental leave, and employer contributions to pension saving schemes.
(13)	Hourly Wage	From 2008-2017: Yearly total labor income (12) divided by yearly hours worked (11). From 1995-2007: Average hourly wage rate in November job. Due to issues with the data quality, we only have reliable hourly wage rates for individuals working more than 20 hours a week in this early part of the sample.
(14)	Job Tenure	Number of years in a row where the main job in November is registered with the same firm identifier.
(15)	Labor Market Experience	Labor market experience measured in years since 1964.
(16)	Public Sector	Dummy indicating work within the public sector (measured by 2-digit industry codes)
(17)	Union Membership	Dummy indicating union membership. Measured by a positive deductible amount reported by the unions to the tax authorities.
(18)	Sick Leave	Share of weeks within a year where the individual (or the individual's employer) have received sickness benefit transfers.
Wealth		
(19)	Debt-to-Income Ratio	"Debt" include debt to banks, pension funds, insurance- and financial companies, credit card debt, and study loans in banks. "Debt" is then divided by labor income (12).
(20)	Savings-to-Income Ratio	"Savings" primarily covers liquid savings and include bank deposits, bond values, and value of mortgage deeds. "Savings" is then divided by labor income (12).
Occupation		
(21)	Physical Ability Requirement	Average importance of Static Strength, Explosive Strength, Dynamic Strength, Trunk Strength, and Stamina, as measured by O*NET. Standardized.
(22)	Cognitive Ability Requirement	Average importance of Fluency of Ideas, Originality, Problem Sensitivity, Deductive Reasoning, Inductive Reasoning, Information Ordering, Category Pleribility, Mathematical Reasoning, and Number Facility, as measured by O*NET. Standardized.
(23)	Injury Rate	Number of accepted (not necessarily compensated) work accidents per full time employee.
Reskilling		
(24)	Access to Higher Education	Defined as having direct access to higher education, either through a high school diploma or a vocational degree. See section 4.1. for more details.
(25)	Travel Time to Higher Education	Shortest travel time in minutes (by car) from the zip code of residence to the zip code of the nearest training facility that offers a relevant higher degree. Travel times are measured as in Harmon (2015). We measure travel times seperately for the "Access" workers in "Craft", "Care", and "Other" educational groups. For workers without access, we impute their travel time as a weighted average of the aforementioned groups based on the zip code of residence.
Injury		
(26)	Earnings Capacity Loss	Loss of earnings capacity in percent as assessed by The Labor Market Insurance (AES). See section 2.1.1. for more details.
(27)	Personal Impairment	Degree of personal impairment in percent based on injury diagnosis. See section 2.1.1. for more details.
(28)	Year of Injury	Calender year of the workplace accident. Non-injured control workers are assigned the year of injury of their matched injured workers.
Primary school grades (at Age 16)		
(29)	Overall GPA	Grade point average of all grades given in grade 9 (compulsory) and grade 10 (not compulsory). Normalized to lie between 0 and 100.
(30)	Math GPA	Grade point average of all grades given in the subject "Math" in grade 9 (compulsory) and grade 10 (not compulsory). Normalized to lie between 0 and 100.
From Main Figures:		
Health outcomes:		
(31)	No. of hospital visits	Number of visits to a hospital, both for admission, outpatient treatment, and ER visits.
(32)	Days in Hospital	Number of days hospitalized. For admitted patients, both the admission- and release date are recorded. Outpatient treatment and ER visits are coded as 1-day visits.
(33)	Pain-Killer Prescription	Dummy indicating a prescription for drugs in the "N02" ATC-classification.
(34)	Antidepressant Prescription	Dummy indicating a prescription for drugs in the "N06A" ATC-classification.
Educational Outcomes		
(35)	Degree courses	Formal education programmes registered in the Education Register (UDDA)
(36)	Non-degree courses	Non-degree courses registered in the Course Participation Register (VEUV)
(37)	Basic	Include courses at Primary- (7) and High School (9) educational programmes.
(38)	Vocational	Include courses at Vocational (8) educational programmes.
(39)	Higher	Include courses at Post-Secondary (10) educational programmes.
(40)	Training Rate	Share of workers enrolling in a higher degree measured within six years after a work accident.
(41)	Participation (flow)	Enrollment in higher degrees in the given year.
(42)	Participation (stock)	Accumulated enrollment in higher degrees.
Labor Market Outcomes:		
(43)	Earnings/Labor Income	Same as (12)
(44)	Earnings + Transfers	Same as (12) + unemployment benefits, sickness benefits, cash assistance, disabillity insurance benefits, public pensions, early retirement benefits, reskilling benefits and state education support.

Notes: This table defines the variables used in the analysis.

Table A.2: Work Accident Sample Reduction

Sample Step	Injury Events	Distinct Individuals	Injury Severity	Earnings Cap. Loss
1. All work accidents with ECL >0	31,129	30,693	12.84	36.18
2. Exclude psychological shock	29,875	29,482	12.77	35.86
3. Collapse to person-year	29,853	29,482	12.78	35.89
4. Person exists in register data	29,783	29,413	12.75	35.88
5. Full time employed before injury	14,623	14,510	12.52	36.57
6. Exclude Military Workers	14,481	14,369	12.45	36.63

Notes: This table shows how our sample restrictions shrink the analysis data, starting from the universe of work accidents that cause loss of earnings capacity from 1998 to 2017. Step 6 corresponds to the "Injury" column of Table 2. For definitions of *earning capacity loss* (ECL), see Section 2.1.

Table A.3: Worker Outcomes before Accident (Relaxing the Matching the Variables)

	Injury	No Injury				
		(1)	(2)	(3)	(4)	(5)
Outcomes in Year -1						
Demographics						
Age	43.32	42.18	41.99	43.32	43.32	43.32
	(10.14)	(10.62)	(10.74)	(10.14)	(10.14)	(10.14)
Female (%)	39.16	45.26	38.75	38.21	39.16	39.16
	(48.81)	(49.78)	(48.72)	(48.59)	(48.81)	(48.81)
Cohabiting (%)	70.62	73.08	71.27	71.95	71.38	71.74
	(45.55)	(44.36)	(45.25)	(44.93)	(45.20)	(45.03)
School-aged Children (%)	33.47	31.99	30.94	32.41	31.81	32.17
	(47.19)	(46.64)	(46.23)	(46.80)	(46.57)	(46.72)
Property Owner (%)	58.57	63.70	60.53	62.31	62.38	61.63
	(49.26)	(48.09)	(48.88)	(48.46)	(48.45)	(48.63)
Education						
Years of Schooling	12.85	13.85	12.96	12.90	12.94	12.91
	(2.63)	(2.88)	(2.87)	(2.93)	(2.90)	(2.56)
Primary (%)	31.54	20.07	28.60	28.82	27.89	31.54
	(46.47)	(40.06)	(45.19)	(45.29)	(44.85)	(46.47)
Vocational (%)	51.18	41.76	49.69	49.24	50.76	51.18
	(49.99)	(49.32)	(50.00)	(50.00)	(50.00)	(49.99)
High School (%)	1.60	4.73	2.73	2.75	2.63	1.60
	(12.53)	(21.23)	(16.31)	(16.35)	(16.01)	(12.53)
Post-Secondary (%)	15.68	33.44	18.98	19.19	18.71	15.68
	(36.36)	(47.18)	(39.21)	(39.38)	(39.00)	(36.36)
Employment						
Hours Worked (Yearly)	1691.64	1727.11	1712.61	1717.66	1715.08	1724.33
	(551.49)	(836.64)	(665.75)	(1061.46)	(759.55)	(862.41)
Labor Income (1000 DKK)	377.40	430.71	377.82	381.46	380.63	380.96
	(126.45)	(229.82)	(147.25)	(136.94)	(139.62)	(142.02)
Hourly Wage	235.01	255.98	232.68	232.73	230.63	227.82
	(172.02)	(181.00)	(356.93)	(217.51)	(139.94)	(126.48)
Job Tenure (Years)	3.62	3.93	3.93	4.01	3.99	4.02
	(3.22)	(3.37)	(3.36)	(3.43)	(3.46)	(3.45)
Labor Market Experience (Years)	19.53	19.48	19.60	20.71	20.64	20.76
	(9.33)	(9.90)	(9.72)	(9.40)	(9.40)	(9.37)
Public Sector (%)	30.07	26.27	30.07	30.07	30.07	30.07
	(45.86)	(44.01)	(45.86)	(45.86)	(45.86)	(45.86)
Union Membership (%)	91.11	81.76	89.72	89.41	89.32	89.77
	(28.46)	(38.62)	(30.37)	(30.78)	(30.88)	(30.31)
Wealth						
Debt-to-Income Ratio (%)	28.49	22.62	24.02	24.15	24.28	23.71
	(27.35)	(25.51)	(25.39)	(25.81)	(25.87)	(25.44)
Savings-to-Income Ratio (%)	14.02	18.34	16.64	16.35	16.64	16.31
	(23.64)	(28.16)	(26.49)	(26.08)	(26.24)	(25.43)
Occupation						
Physical Ability Requirement (Std.)	0.75	-0.07	0.71	0.72	0.72	0.71
	(0.93)	(1.09)	(0.92)	(0.92)	(0.92)	(0.92)
Cognitive Ability Requirement (Std.)	-0.39	0.09	-0.36	-0.35	-0.36	-0.37
	(0.84)	(0.96)	(0.86)	(0.86)	(0.86)	(0.86)
Injury Rate (x 1000)	10.35	6.16	9.98	10.07	10.08	10.08
	(5.03)	(4.76)	(4.61)	(4.96)	(5.07)	(4.94)
Reskilling						
Access to Higher Education (%)	48.82	57.51	52.33	52.03	52.70	48.82
	(49.99)	(49.43)	(49.95)	(49.96)	(49.93)	(49.99)
Travel Time to Higher Education (Min.)	34.08	40.49	33.97	33.58	34.02	33.49
	(24.29)	(44.37)	(26.62)	(25.21)	(25.21)	(24.84)
Injury						
Earnings Capacity Loss (%)	36.58	0.00	0.00	0.00	0.00	0.00
	(22.20)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Personal Impairment (%)	12.44	0.00	0.00	0.00	0.00	0.00
	(10.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Year of Injury	2004.92	2004.92	2004.92	2004.92	2004.92	2004.92
	(4.84)	(4.84)	(4.84)	(4.84)	(4.84)	(4.84)
Match variables						
Year		✓	✓	✓	✓	✓
Occupation			✓	✓	✓	✓
Age				✓	✓	✓
Gender					✓	✓
Education						✓
Observations	14481	14481	14481	14481	14481	14481

Notes: This figure shows how the comparison of "Injury" and "No Injury" workers (Table 2) are affected by relaxing which covariates that workers are required to match on. Workers are one-to-one matched in the specified cells. Specification 1 matches workers on the year of the event. Specification 2 also matches workers on their occupation before the event. Specification 3 furthermore matches workers' age. Specification 4 furthermore matches workers' gender. Specification 5 (our baseline specification) also matches workers' level of education.

Table A.4: Human Capital Investment by Educational Background of Workers

		Accumulated Participation (FTE, Diff-in-Diff, Year +10)					
		Degrees			Courses		
	Percent of Injuries	Basic	Vocational	Higher	Basic	Vocational	Higher
Primary	31.5	0.021	-0.009	0.019	0.009	-0.002	0.000
		(0.003)	(0.005)	(0.004)	(0.002)	(0.001)	(0.001)
Vocational							
w/o Access	19.6	0.038	0.012	0.031	0.012	0.001	0.011
		(0.005)	(0.008)	(0.006)	(0.003)	(0.002)	(0.006)
w/ Access	31.5	0.024	0.018	0.107	0.010	-0.001	0.002
		(0.003)	(0.005)	(0.007)	(0.002)	(0.002)	(0.002)
Secondary	1.6	-0.018	0.006	0.099	0.024	0.003	-0.006
		(0.018)	(0.034)	(0.040)	(0.010)	(0.006)	(0.008)
Post-Secondary	15.6	0.005	0.005	0.037	0.012	0.001	-0.004
		(0.003)	(0.004)	(0.008)	(0.003)	(0.001)	(0.006)

Notes: This table shows the completion of education (measured in full-year equivalents) ten years after work accidents. The estimates are the difference-in-differences in outcomes (measured relative to year -1) between the "Injury" and "Match" workers from Table 2, estimated using the regression equation (1). Standard errors are reported in parentheses.

Table A.5: Vocational Degrees with Access to Higher Education

Group	**Vocational Degree**	**Share of Injuries (%)**	**Share of Reskilling (%)**	**Vocational Occupation**	**Access Degree**	**Access Occupation**
Craft Workers	Carpentry	14.4	26.3	7124 Carpenters and Joiners	Construction Architecture (BA)	3112 Civil Engineering Technicians
	Electrician	6.0	6.9	7137 Electrician Work	Service Engineering (AP)	3113 Electrical Engineering Technicians
	Welder	5.6	5.7	7222 Tool-makers and related workers	Production Technology (AP)	3000 Technicians, n.e.c.
Care Workers	Social-Health Assistant	7.5	8.2	5132 Care Work at Institutions	Social Worker (BA)	3460 Social Work Associates
	Pedagogical Assistant	0.4	0.3	5131 Childcare Work	Social Education (BA)	3320 Pre-Primary Education Teachers
Other Workers	Retail, Groceries	4.8	2.3	5220 Salespersons and Demonstrators	Commerce Management (AP)	3140 Sales and Finance Work
	Cook	1.6	1.8	5122 Cooks	Nutrition & Technology (AP)	3000 Technicians, n.e.c.
	Nutrition Assistant	1.0	1.5	5122 Cooks	Nutrition & Technology (AP)	3000 Technicians, n.e.c.

Notes: This table lists the top-3 vocational degrees among education groups that give access to higher education. The full list of vocational degrees with access to higher education is available at `www.andershumlum.com/s/access_list.xlsx`.

Table A.6: Share of Injuries and Reskilling by Educational Group (Vocational Degrees with Access to Higher Education)

	Share of Injuries (%)	Share of Reskilling (%)
Craft Workers	71.0	78.0
Care Workers	8.0	8.5
Other Workers	21.0	13.5
Retail	13.1	5.4
Food & Agriculture	7.9	8.0

Notes: This table shows the share of education groups among injured workers whose vocational education gives access to higher education. See Table for A.5 for the top-3 vocational degrees in each education group.

Table A.7: Worker Outcomes at Age 16

	Access	No Access		Std. Diff
		Raw	IPW	Access - IPW
Outcomes at Age 16				
Primary school grades				
Overall GPA (0-100)	50.76	50.77	51.77	-10.6%
	(8.95)	(10.57)	(9.93)	
Math GPA (0-100)	54.57	49.64	53.92	5.3%
	(10.14)	(12.83)	(14.03)	
Employment				
Employed (%)	76.86	68.87	73.43	8.0%
	(41.37)	(46.37)	(44.18)	
Labor Income (1000 DKK)	49.41	39.35	44.69	12.3%
	(38.52)	(36.49)	(38.16)	
Parental Education				
Years of Schooling	11.54	11.31	11.54	-0.2%
	(2.69)	(2.82)	(2.77)	
Primary (%)	27.55	31.58	27.89	-0.8%
	(44.68)	(46.54)	(44.87)	
Vocational (%)	54.58	50.53	54.60	0.0%
	(49.77)	(50.06)	(49.82)	
High School (%)	0.75	0.53	0.50	3.4%
	(8.20)	(7.25)	(6.83)	
Post-Secondary (%)	16.26	16.32	16.49	-0.6%
	(36.95)	(37.00)	(37.11)	
Parental Employment				
Labor Income (1000 DKK)	471.10	463.83	479.86	-3.5%
	(258.08)	(235.51)	(237.76)	
Both Employed (%)	67.08	62.89	66.94	0.3%
	(46.95)	(48.37)	(47.07)	
At Least One Employed (%)	92.93	89.47	94.57	-6.9%
	(25.28)	(30.73)	(22.58)	
Parental Wealth				
Debt-to-Income Ratio (%)	34.97	35.09	34.49	1.4%
	(35.45)	(32.54)	(32.74)	
Savings-to-Income Ratio (%)	15.18	15.34	15.44	-0.9%
	(27.75)	(30.02)	(31.19)	
Observations	1079	436	436	

Notes: This table shows the characteristics of workers at age 16, the time at which they decided on their vocational training. The table has fewer observations than Table 3 because primary school grades are only observed for workers who graduated after 2002. Standard deviations are in parentheses. The "Access" column shows workers eligible for a higher degree (but have not attained one). The "No Access" columns show workers ineligible for a higher degree. The "IPW" column implements an Inverse Probability Weighing (IPW) of the workers according to a logistic regression of access to higher degrees on the covariates reported in this table. Appendix C details the IPW procedure. The "Std. Mean Diff" column shows the standardized mean difference between the "Access" and "IPW" workers with absolute values above 25% indicative of imbalance (Stuart and Rubin (2008)).

Table A.8: Injury Characteristics by Access Group

	Access	No Access		Std. Diff.
		Raw	IPW	Access - IPW
Body Part (%)				
Head	5.63	6.50	6.65	-4.3%
	(23.01)	(24.67)	(24.90)	
Neck	5.91	6.47	6.10	-0.8%
	(23.47)	(24.60)	(23.94)	
Back	33.60	36.92	33.86	-0.5%
	(47.10)	(48.27)	(47.21)	
Torso	3.68	2.99	2.71	5.5%
	(18.79)	(17.03)	(16.25)	
Upper Extremities	25.70	24.37	23.30	5.6%
	(43.68)	(42.94)	(42.28)	
Lower Extremities	17.51	14.28	17.39	0.3%
	(37.65)	(34.99)	(37.79)	
Multiple Body Parts	6.39	7.21	7.95	-6.1%
	(24.43)	(25.87)	(27.06)	
Other/Unknown	1.58	1.27	2.03	-3.4%
	(12.42)	(11.18)	(14.05)	
Injury Event (%)				
Contact with Dangerous Matter	0.96	0.63	0.96	0.0%
	(9.57)	(7.93)	(9.62)	
Suffocation	0.02	0.04	0.01	1.6%
	(1.25)	(1.88)	(0.50)	
Falling	36.84	29.64	32.76	8.7%
	(47.62)	(45.68)	(46.65)	
Collision	12.78	12.66	15.15	-6.8%
	(33.26)	(33.26)	(35.80)	
Cutting	4.23	3.41	4.15	0.4%
	(19.83)	(18.15)	(19.75)	
Crushing	2.04	1.65	2.92	-5.7%
	(14.04)	(12.75)	(16.66)	
Acute Physical Strain	29.51	37.13	30.89	-3.1%
	(44.57)	(48.32)	(45.70)	
Attacks (from humans or animals)	1.09	2.22	1.39	-2.9%
	(9.30)	(14.72)	(11.12)	
Other/Unknown	12.52	12.62	11.77	2.3%
	(33.08)	(33.22)	(32.23)	
Observations	4568	2844	2844	

Notes: This table shows the characteristics of accidents (affected body part and cause of injury events, as assessed by AES) by workers' access to higher education. Standard deviations are in parentheses. The "Std. Mean Diff" column shows the standardized mean difference between the "Access" and "IPW" workers, where absolute values above 25% is a standard threshold for assessing imbalance (Stuart and Rubin (2008)).

Table A.9: Profiling Workers by Their Reskilling after Injuries

	Average	Compliers	Always-takers	Never-takers
Outcomes in Year -1				
Demographics				
Age	42.03	31.56	32.16	43.84
	(0.14)	(0.25)	(0.55)	(0.20)
Female (%)	3.63	10.89	11.93	2.35
	(0.24)	(0.63)	(2.72)	(0.29)
Cohabiting (%)	73.01	67.15	74.05	73.88
	(0.58)	(1.59)	(3.68)	(0.84)
School-aged Children (%)	30.78	31.87	34.45	30.54
	(0.60)	(1.59)	(3.99)	(0.88)
Property Owner (%)	70.32	57.03	59.07	72.58
	(0.60)	(1.67)	(4.13)	(0.85)
Education				
Years of Schooling	14.40	14.35	14.31	14.41
	(0.00)	(0.01)	(0.03)	(0.00)
Primary (%)	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Vocational (%)	100.00	100.00	100.00	100.00
	(0.00)	(0.00)	(0.00)	(0.00)
High School (%)	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Post-Secondary (%)	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Employment				
Hours Worked (Yearly)	1674.94	1556.91	1589.12	1694.69
	(8.36)	(16.07)	(36.96)	(13.11)
Labor Income (1000 DKK)	401.16	377.81	374.59	405.28
	(1.58)	(3.83)	(10.20)	(2.30)
Hourly Wage (DKK)	256.20	283.32	225.94	252.74
	(3.12)	(18.15)	(6.80)	(0.97)
Job Tenure (Years)	4.10	3.16	2.67	4.27
	(0.05)	(0.07)	(0.18)	(0.07)
Labor Market Experience (Years)	20.92	11.98	14.27	22.42
	(0.12)	(0.24)	(0.57)	(0.17)
Public Sector (%)	4.56	7.19	9.36	4.05
	(0.27)	(0.58)	(2.44)	(0.38)
Sick Leave (% of weeks)	4.35	3.95	2.57	4.45
	(0.14)	(0.31)	(0.57)	(0.22)
Wealth				
Debt-to-Income Ratio (%)	41.17	38.10	54.43	41.35
	(0.65)	(1.67)	(5.02)	(0.97)
Savings-to-Income Ratio (%)	20.20	11.96	13.39	21.60
	(0.77)	(1.20)	(1.93)	(1.25)
Occupation				
Physical Ability Requirement (Std.)	0.99	1.03	0.85	0.99
	(0.01)	(0.03)	(0.07)	(0.02)
Cognitive Ability Requirement (Std.)	-0.37	-0.31	-0.38	-0.38
	(0.01)	(0.03)	(0.06)	(0.01)
Injury Rate (x 1000)	11.39	11.53	10.41	11.39
	(0.06)	(0.00)	(0.38)	(0.09)
Reskilling				
Access to Higher Education (%)	84.16	100.00	0.00	100.00
	(0.48)	(0.00)	(0.00)	(0.00)
Travel Time to Higher Education (Min.)	36.08	31.26	36.71	36.80
	(0.33)	(0.85)	(1.62)	(0.50)
Share of Injuries	100.0%	12.9%	1.9%	85.2%

Notes: This table characterizes injured workers according to their potential decisions after injuries. Standard errors are in parentheses. Reskilling is defined as enrolling in a higher degree within ten years after the accident. *Compliers* reskill only if they have direct access to higher education. *Always-takers* reskill regardless of their access to higher education. *Never-takers* do not reskill regardless of their access to higher education.

Table A.10: Profiling Workers by Their Reskilling after Injuries

	Average	Compliers	Always-takers	Never-takers
Outcomes at Age 16				
Primary school grades				
Overall GPA (0-100)	51.03	64.82	64.82	48.64
	(1.06)	(1.24)	(2.01)	(1.85)
Math GPA (0-100)	55.42	65.33	71.58	53.56
	(1.34)	(1.67)	(4.77)	(2.29)
Employment				
Employed (%)	80.25	68.72	80.08	82.00
	(1.18)	(2.11)	(5.34)	(1.72)
Labor Income (1000 DKK)	40.81	29.20	44.91	42.48
	(0.91)	(1.72)	(4.67)	(1.31)
Parental Education				
Years of Schooling	11.57	11.90	12.35	11.51
	(0.27)	(0.14)	(0.36)	(0.13)
Primary (%)	26.51	27.33	26.05	26.40
	(1.31)	(2.30)	(5.87)	(1.97)
Vocational (%)	0.86	2.34	2.44	0.60
	(0.27)	(0.65)	(2.06)	(0.35)
High School (%)	56.15	50.40	48.11	57.20
	(1.47)	(2.61)	(6.68)	(2.21)
Post-Secondary (%)	15.90	22.11	23.39	14.80
	(1.09)	(2.03)	(5.66)	(1.59)
Parental Employment				
Labor Income (1000 DKK)	374.89	466.61	450.97	359.34
	(6.67)	(12.89)	(26.72)	(9.65)
Both Employed (%)	68.74	64.21	70.19	69.40
	(1.38)	(2.44)	(6.11)	(2.06)
At Least One Employed (%)	94.19	93.93	95.75	94.20
	(1.05)	(1.05)	(1.05)	(1.05)
Parental Wealth				
Debt-to-Income Ratio (%)	33.68	39.44	31.02	32.86
	(1.14)	(2.03)	(5.43)	(1.72)
Savings-to-Income Ratio (%)	15.77	21.87	10.67	14.95
	(0.97)	(1.60)	(1.87)	(1.52)
Share of Injuries	100.0%	12.9%	1.9%	85.2%

Notes: This table characterizes injured workers according to their reskilling decisions after injuries. Reskilling is defined as enrolling in a higher degree within ten years after the accident. *Compliers* reskill only if they have direct access to higher education. *Always-takers* reskill regardless of their access to higher education. *Never-takers* do not reskill regardless of their access to higher education.

Table A.11: Job Characteristics of Compliers

	Standard deviations from Economy Average		Change in Percent
	Year -1	Year +10	Year -1 to +10
Injury + Reskill			
Physical Ability Requirements	1.670	-0.261	
	(0.265)	(0.311)	
Cognitive Ability Requirements	-0.002	0.710	
	(0.207)	(0.320)	
Earnings	-0.181	0.384	25.3
	(0.190)	(0.217)	(9.7)
Occupational Earnings Premium	-0.240	1.433	76.8
	(0.089)	(0.313)	(14.4)
No Injury			
Physical Ability Requirements	1.702	0.875	
	(0.197)	(0.228)	
Cognitive Ability Requirements	-0.034	0.017	
	(0.163)	(0.201)	
Earnings	-0.251	0.212	21.4
	(0.122)	(0.151)	(7.0)
Occupational Earnings Premium	-0.364	0.192	27.1
	(0.080)	(0.093)	(4.5)

Notes: This table shows the job characteristics of workers who are employed ten years after a work accident. The "Injury & Reskill" panel reports treated complier means, estimated using Equation (4). The "No Injury" panel reports the outcomes of their match workers (who do not experience a work injury in the event year). *Physical Ability* is defined as the average importance of Static Strength, Explosive Strength, Dynamic Strength, Trunk Strength, and Stamina, as measured by O*NET. *Cognitive Ability* is defined as the average importance of Fluency of Ideas, Originality, Problem Sensitivity, Deductive Reasoning, Inductive Reasoning, Information Ordering, Category Pleribility, Mathematical Reasoning, and Number Facility, as measured by O*NET. We calculate "Occupational Earnings Premium" as the average labor market earnings within each "Match" (Year-Occupation-Industry-Education-Age-Gender) cell in the full population of non-injured workers with at least three years of full-time work leading up to year -1. Columns 1 and 2 are measured in standard deviations from the average occupational earnings premium of the "No Injury" workers matched on calendar year in Table A.3 (Column (1)). Column 3 reports the percent change in the worker's outcome.

Table A.12: Scenarios for Compliers: Present-Discounted Values

	Injury & Reskill	No Injury	No Injury & Reskill
Workers	**557,530**	**564,203**	**568,029**
Earnings	454,175	542,257	518,121
Transfers	58,889	18,629	32,762
Educ. Transfers	44,465	3,317	17,146
Government	**77,593**	**234,855**	**168,421**
Educ. Transfers + Tuition	-81,552	-6,834	-47,549
Transfers	-58,889	-18,629	-32,762
Taxes	218,033	260,318	248,731
Total	**635,122**	**799,058**	**736,450**

Notes: This table shows the present-discounted values generated by compliers (i.e., workers who respond to the access policy by reskilling after injuries) in different scenarios. The present-discounted values assume a real discount rate of 6% per year. *Earnings* are labor earnings after tax, *Transfers* include disability benefits, unemployment benefits, sickness benefits, and cash assistance, *Educ. Transfers* include reskilling benefits and State Education Support (SU), *Educ. Transfers + Tuition* expenses include tuition and education transfers, and *Taxes* refer to labor income taxes. The "Injury & Reskill" column reports treated complier means, estimated using Equation (4). The "No Injury" column reports the outcomes of their match workers (who do not experience a work injury in the event year). The "No Injury & Reskill" is based on the "Injury & Reskill" column with two adjustments: (1) injured workers who are on sick leave in years 0-3 or disability insurance in years 3 and onward after the accidents are assigned the outcomes of their match workers (for income, transfers, and educ. transfers), and (2) workers in school receive the standard SU stipend (instead of the higher reskilling benefits which are only available for injured workers).

Table A.13: Propensity Score Estimation

	Dependent var.: Reskilling in year $\in$ [0,10]
Age	0.282
	(0.049)
Access = 1	4.766
	(0.918)
Access $\times$ Age	-0.192
	(0.051)
Age^2	-0.006
	(0.001)
Access $\times$ Age^2	0.003
	(0.001)
TravelTime	0.017
	(0.003)
Access $\times$ TravelTime	-0.025
	(0.004)
TravelTime^2	-0.000
	(0.000)
Access $\times$ TravelTime^2	0.000
	(0.000)
Constant	-5.591
	(0.881)
Event-year FEs	✓
F-stat on 'Access' interaction terms	15.49

Notes: This table reports the propensity score estimation results (Equations (12)-(14)). Robust standard errors in parentheses.

Table A.14: Estimation of Private Benefits

Dep. var.: Private Benefits: After-tax labor market earnings + education transfers ($1,000)											
Years since Accident	0	1	2	3	4	5	6	7	8	9	10
$\hat{p}$	-8.66	0.39	3.12	23.02***	28.82***	43.40***	54.03***	29.63**	33.84***	31.13**	18.55
	(7.63)	(10.00)	(10.95)	(8.37)	(9.26)	(10.48)	(11.11)	(11.49)	(12.65)	(14.69)	(15.61)
$\hat{p}^2/2$	7.11	-36.51	20.50	-56.34**	-71.98**	-120.89***	-150.87***	-59.86	-78.22*	-60.29	9.35
	(24.34)	(31.83)	(32.70)	(26.11)	(30.14)	(35.84)	(37.85)	(37.83)	(43.15)	(50.24)	(53.23)
Observations	3,518	3,518	3,466	3,401	3,327	3,230	3,119	2,984	2,791	2,608	2,335

Notes: This table shows the reduced-form estimation results (Equation (16)) for the private benefits of reskilling (post-tax labor earnings and reskilling benefits). Control variables are not displayed. Standard errors in parentheses are estimated with a Bayesian bootstrap (Shao and Tu (2012)) of 1000 iterations over the propensity score and outcome equations (12)-(14) and (16) with weights drawn from a uniform distribution, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.15: Estimation of Private Costs

Dep. var.: Private Costs: Lost public transfers ($1,000)											
Years since Accident	0	1	2	3	4	5	6	7	8	9	10
$\hat{p}$	-2.80	8.60**	17.23***	19.20***	20.15***	18.85***	14.98***	13.38***	13.91**	17.74***	16.13***
	(3.18)	(4.00)	(4.52)	(4.26)	(4.23)	(4.54)	(4.83)	(4.84)	(5.48)	(5.58)	(5.99)
$\hat{p}^2/2$	16.05	-21.67	-28.74*	-36.01**	-38.92***	-47.81***	-34.29**	-22.78	-21.72	-32.07*	-20.69
	(10.68)	(13.71)	(15.36)	(14.27)	(13.84)	(15.72)	(16.49)	(15.75)	(18.40)	(18.87)	(19.88)
Observations	3,518	3,518	3,466	3,401	3,327	3,230	3,119	2,984	2,791	2,608	2,335

Notes: This table shows the reduced-form estimation results (Equation (16)) for the private costs of reskilling (lost public benefits). Control variables are not displayed. Standard errors in parentheses are estimated with a Bayesian bootstrap (Shao and Tu (2012)) of 1000 iterations over the propensity score and outcome equations (12)-(14) and (16) with weights drawn from a uniform distribution, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.16: Estimation of Public Benefits

Dep. var.: Public Benefits: Tax income + avoided public transfers ($1,000)											
Years since Accident	0	1	2	3	4	5	6	7	8	9	10
$\hat{p}$	-6.96	6.87	14.89*	29.34***	33.65***	41.17***	44.34***	30.46***	30.15***	32.68***	25.04**
	(6.15)	(8.05)	(8.12)	(7.25)	(7.71)	(8.69)	(9.38)	(9.50)	(10.64)	(11.59)	(12.27)
$\hat{p}^2/2$	19.28	-37.83	-21.35	-78.05***	-87.67***	-121.27***	-127.20***	-67.96**	-59.27*	-61.02	-16.21
	(20.01)	(26.68)	(25.93)	(23.66)	(25.26)	(30.12)	(32.08)	(30.86)	(35.55)	(39.30)	(41.19)
Observations	3,518	3,518	3,466	3,401	3,327	3,230	3,119	2,984	2,791	2,608	2,335

Notes: This table shows the reduced-form estimation results (Equation (16)) for the public benefits of reskilling (tax income and lost public transfers). Control variables are not displayed. Standard errors in parentheses are estimated with a Bayesian bootstrap (Shao and Tu (2012)) of 1000 iterations over the propensity score and outcome equations (12)-(14) and (16) with weights drawn from a uniform distribution, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

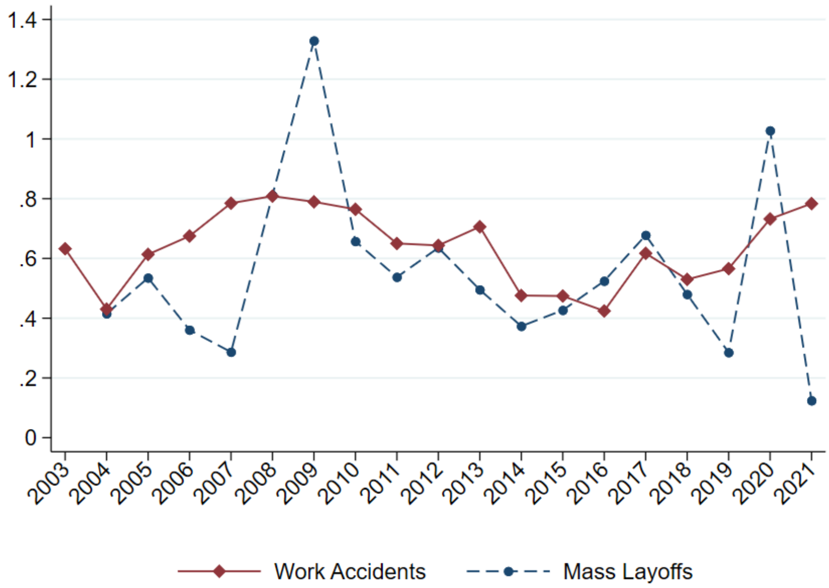
Table A.17: Estimation of Public Costs

Dep. var.: Public Costs: Education cost + educational transfers ($1,000)											
Years since Accident	0	1	2	3	4	5	6	7	8	9	10
$\hat{p}$	-0.51	10.05**	18.73***	8.84	1.46	-5.09	-9.98*	-9.14***	0.00	0.00	0.00
	(1.23)	(4.01)	(6.24)	(6.32)	(6.23)	(5.60)	(5.20)	(3.85)	(0.00)	(0.00)	(0.00)
$\hat{p}^2/2$	1.10	-4.69	2.76	49.91**	61.35***	54.89***	69.81***	49.19***	0.00	0.00	0.00
	(4.29)	(14.97)	(23.37)	(24.27)	(23.74)	(20.61)	(19.24)	(15.12)	(0.00)	(0.00)	(0.00)
Observations	3,518	3,518	3,466	3,401	3,327	3,230	3,119	2,984	2,791	2,608	2,335

Notes: This table shows the reduced-form estimation results (Equation (16)) for the public costs of reskilling (tuition and reskilling benefits). We set the estimates to zero after year 8 since workers do not participate in education after that point (Figure 5.(a)). Standard errors in parentheses are estimated with a Bayesian bootstrap (Shao and Tu (2012)) of 1000 iterations over the propensity score and outcome equations (12)-(14) and (16) with weights drawn from a uniform distribution, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

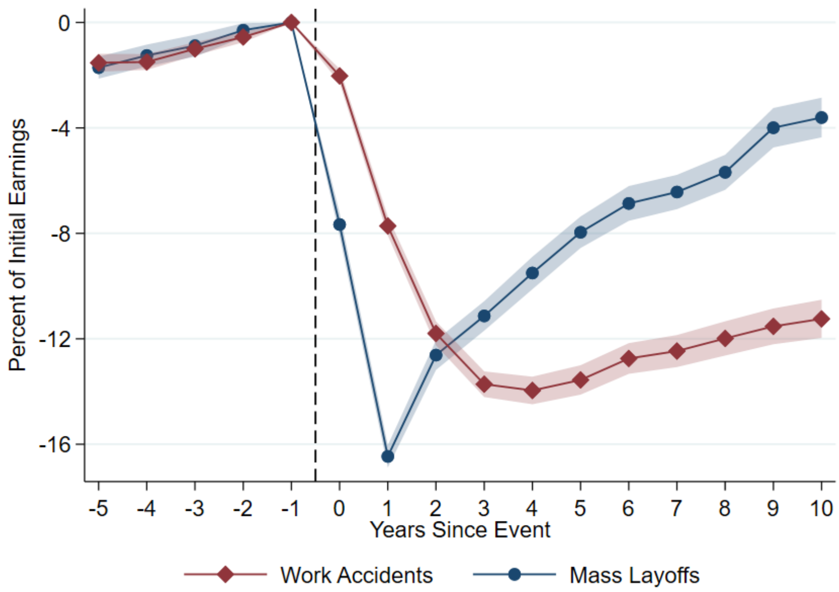
A.2 Figures

Figure A.1: Work Accidents and Mass Layoffs per 100 Workers



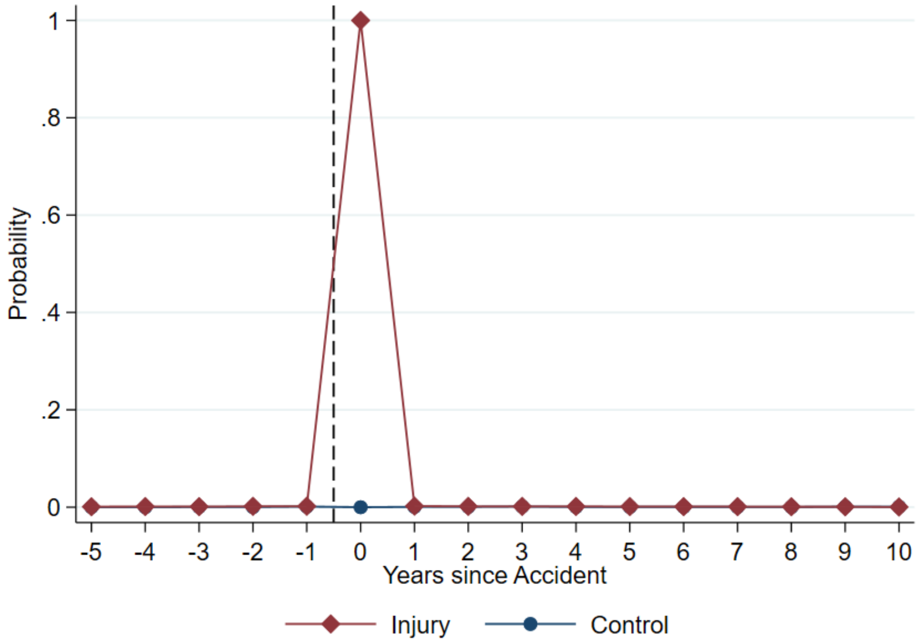
Notes: This figure shows the number of workers who experience a work accident or mass layoff in percent of the total employment in Denmark. The graphs are based on public data from the AES and the Danish Agency for Labour Market and Recruitment.

Figure A.2: Labor Earnings around Work Accident vs. Mass Layoff



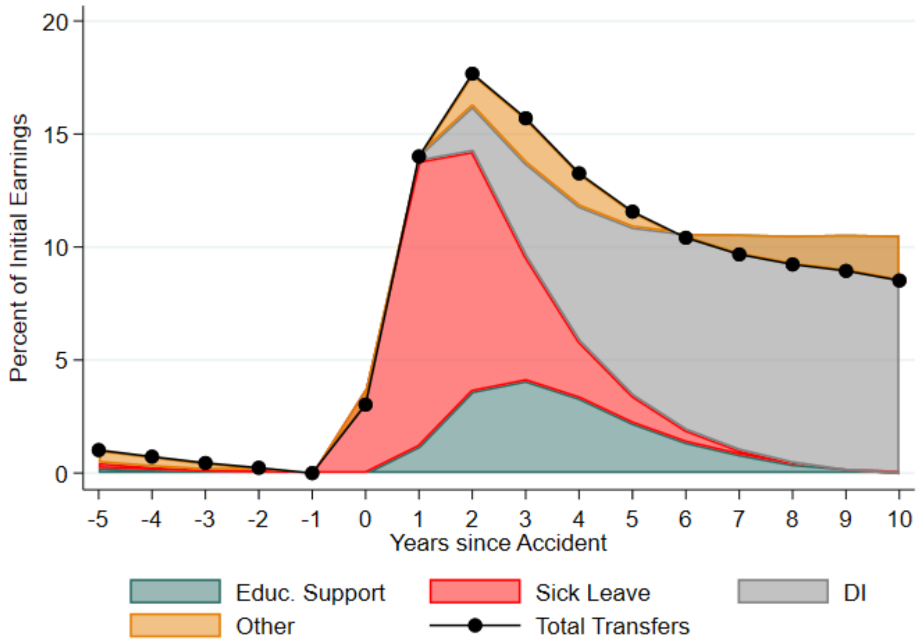
Notes: This figure compares the labor earnings of workers around work accidents and mass layoffs. Mass layoffs are defined as in Davis and Von Wachter (2011). We include all work accidents accepted with compensation. We match each injured/displaced worker to a control worker, following the procedure in Table 2. The graphs show the differences-in-differences in outcomes between the injured/displaced workers and their matches. Shaded areas represent 95% confidence bands, estimated using the regression equation (1).

Figure A.3: Probability of Work Accident



Notes: This figure shows the probability of work accidents (causing loss of physical earning capacity) in event time. The "Control" workers correspond to the "Match" column in Table 2.

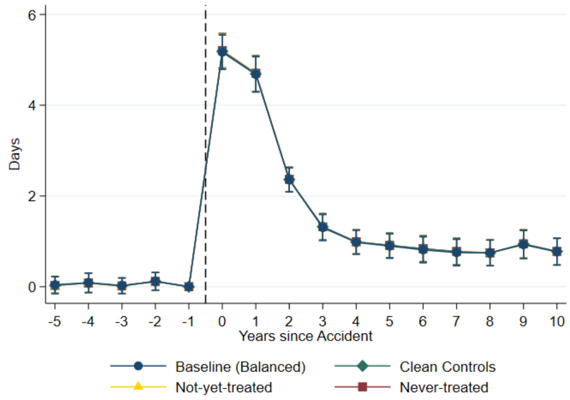
Figure A.4: Receipt of Public Transfers around Accident



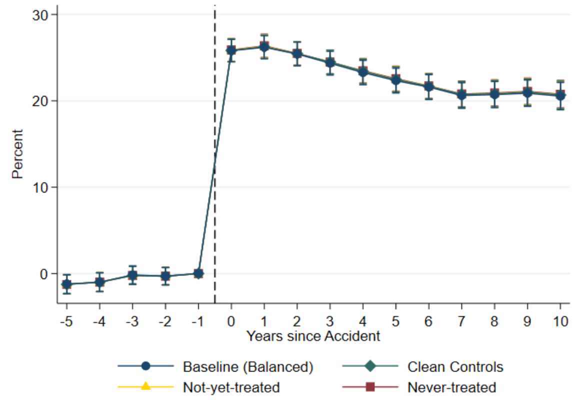
Notes: This figure splits the effect of work accidents on the receipt of transfers by public programs. *Educ. Support* is reskilling benefits and SU, *Sick Leave* is sickness benefits, *DI* is disability insurance, and *Other* is mainly unemployment insurance. The figure shows the differences-in-differences in outcomes (measured relative to year -1) between the "Injury" and "Match" workers from Table 2.

Figure A.5: Worker Outcomes around Accident (Comparison of Estimators)

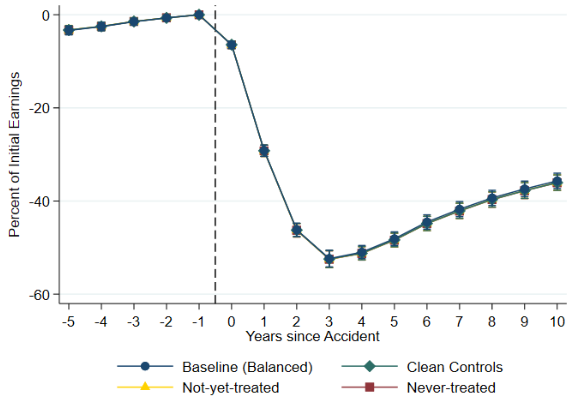
(a) Days in Hospital



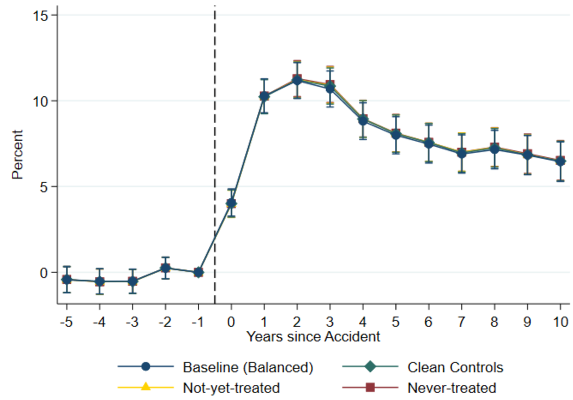
(b) Pain-Killer Prescription



(c) Income

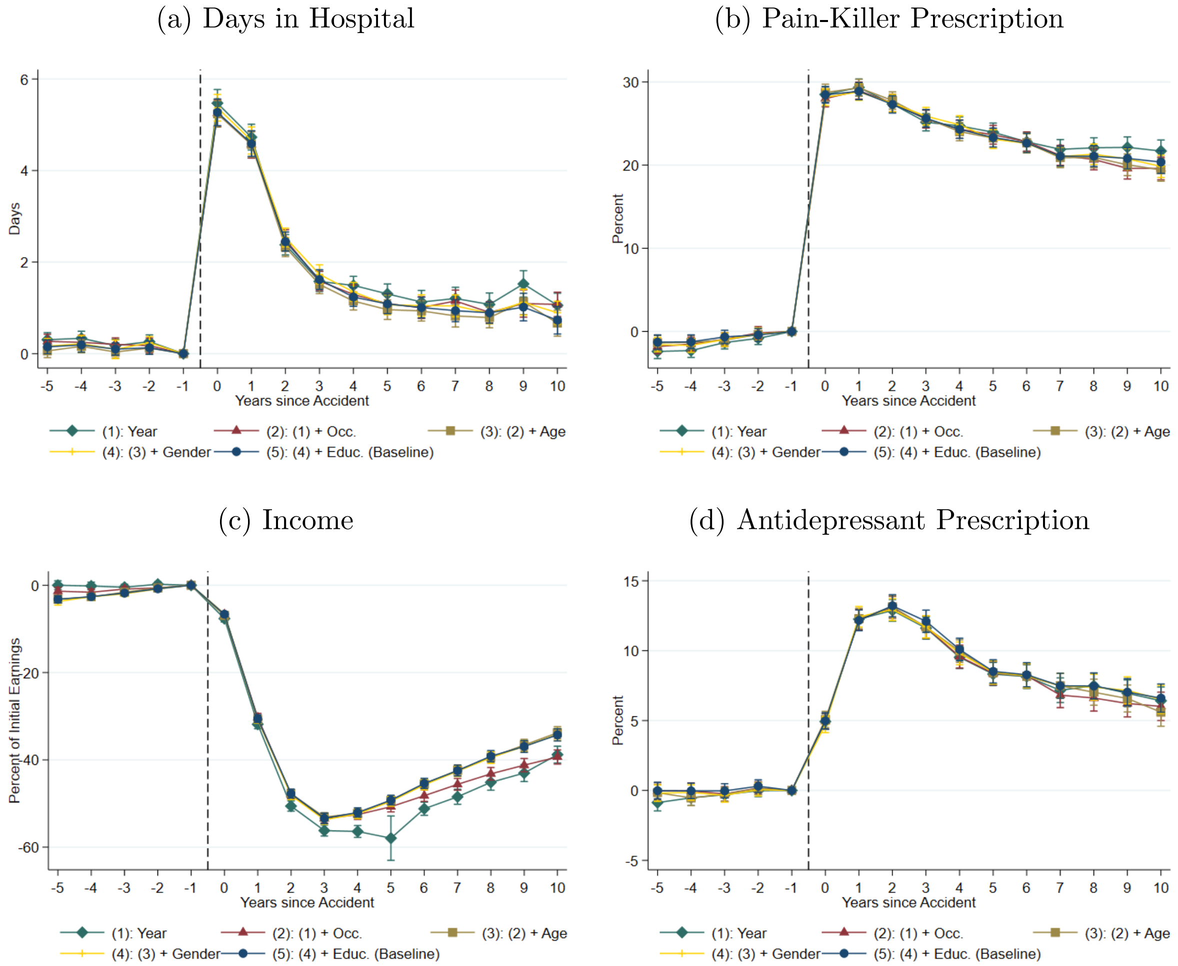


(d) Antidepressant Prescription



Notes: This figure compares our baseline estimates (Figure 1) with estimators that address identification issues that may arise in difference-in-differences designs when treatments are staggered (Gardner (2022); Roth et al. (2022); De Chaisemartin and d'Haultfoeuille (2022b)). The estimators impose successively stricter requirements on the treatment and control groups. "Baseline (Balanced)" plots our baseline estimates on a balanced sample from years -5 to 10 (the event window). "Clean Controls" requires that control workers are not treated in the event window, corresponding to the specification in Cengiz et al. (2019). "Not-yet-treated" focuses on the first events of our treatment group and further requires that control workers are not treated before or during the event window, corresponding to the estimators developed in (Callaway and Sant'Anna (2021); De Chaisemartin and d'Haultfoeuille (2022a)). "Never-treated" further requires that control workers are not treated throughout our data period, corresponding to the estimators developed in Callaway and Sant'Anna (2021) Sun and Abraham (2021), and De Chaisemartin and d'Haultfoeuille (2022a).

Figure A.6: Worker Outcomes around Accident (Relaxing the Matching Variables)

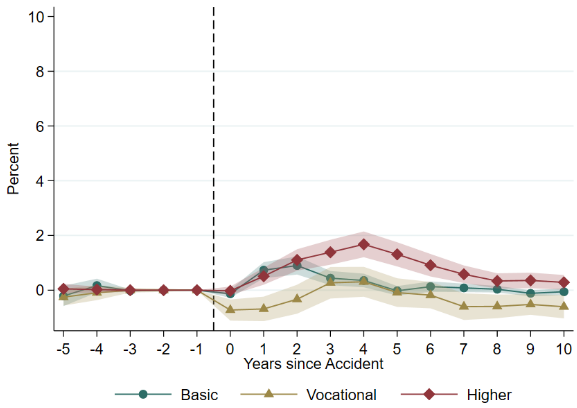


Notes: This figure shows how the difference-in-differences estimates of the impact of work accidents (Figure 1) are affected by relaxing which covariates that injured and control workers are required to match on. Injured and control workers are one-to-one matched in the specified cells. Specification 1 matches workers on the year of the event. Specification 2 also matches workers on their occupation before the event. Specification 3 furthermore matches workers' age. Specification 4 furthermore matches workers' gender. Specification 5 (our baseline specification) also matches workers' level of education.

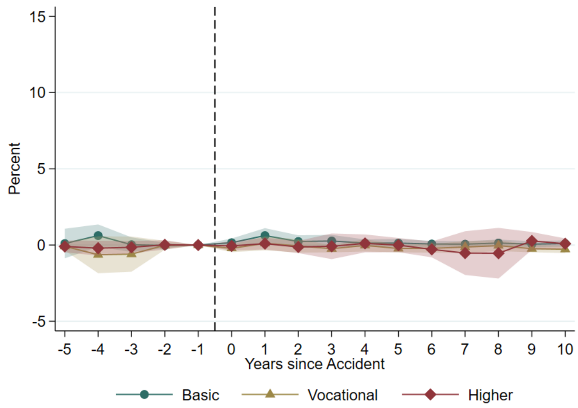
Figure A.7: Human Capital Investment by Educational Background of Workers

(a) Initial Attainment: Primary School

Degree

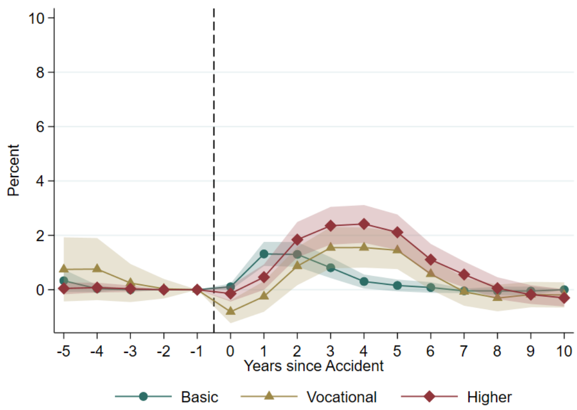


Non-Degree

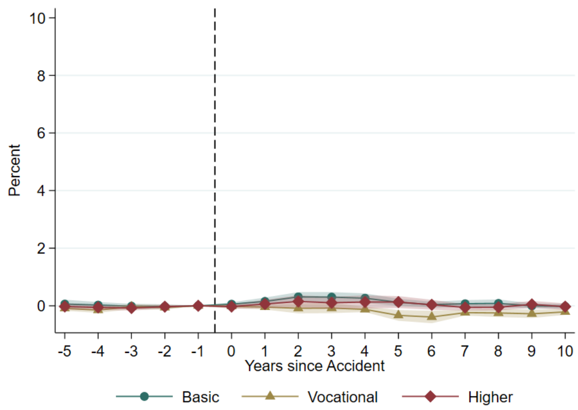


(b) Initial Attainment: Vocational Degree without Access to Higher Education

Degree

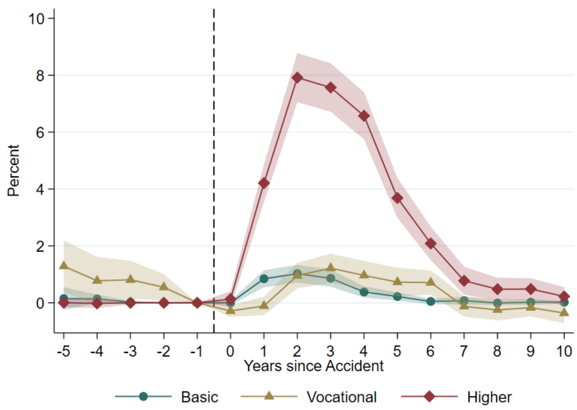


Non-Degree

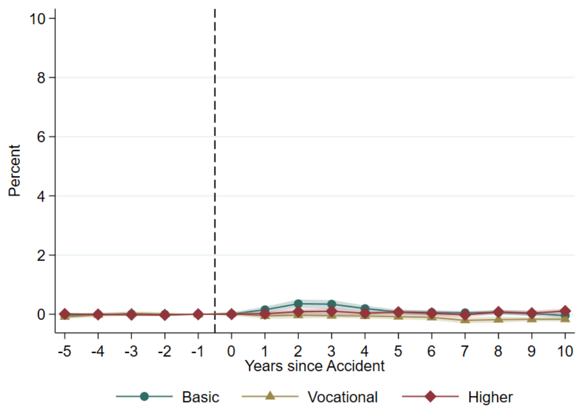


(c) Initial Attainment: Vocational Degree with Access to Higher Education

Degree



Non-Degree

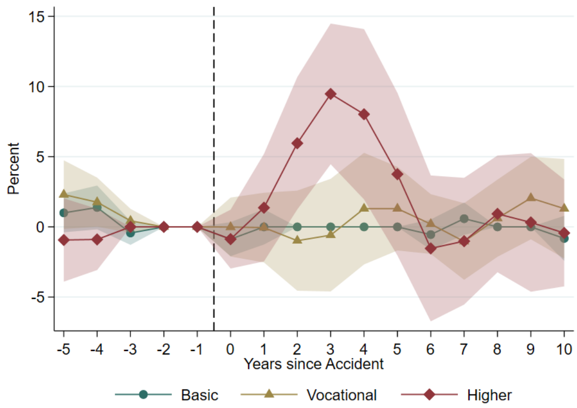


Notes: This table continues on the next page.

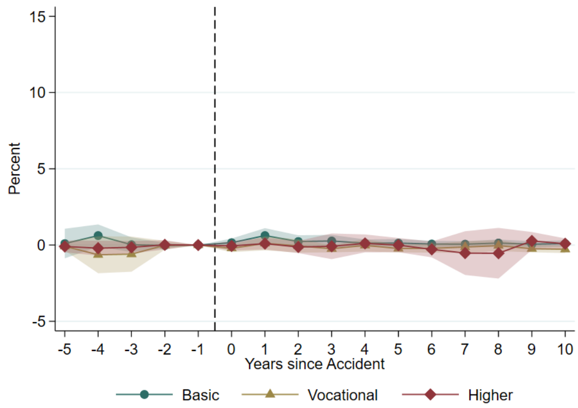
Figure A.7 (Cont.): Human Capital Investment by Educational Background of Workers

(a) Initial Attainment: High School

Degree

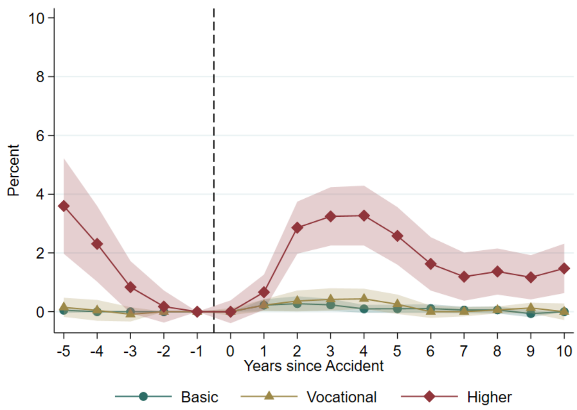


Non-Degree

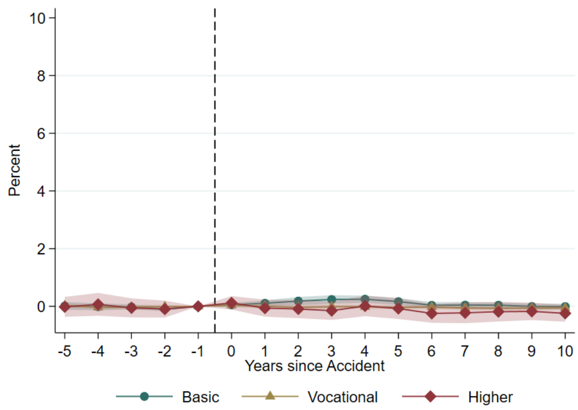


(b) Initial Attainment: Post-Secondary Degree

Degree

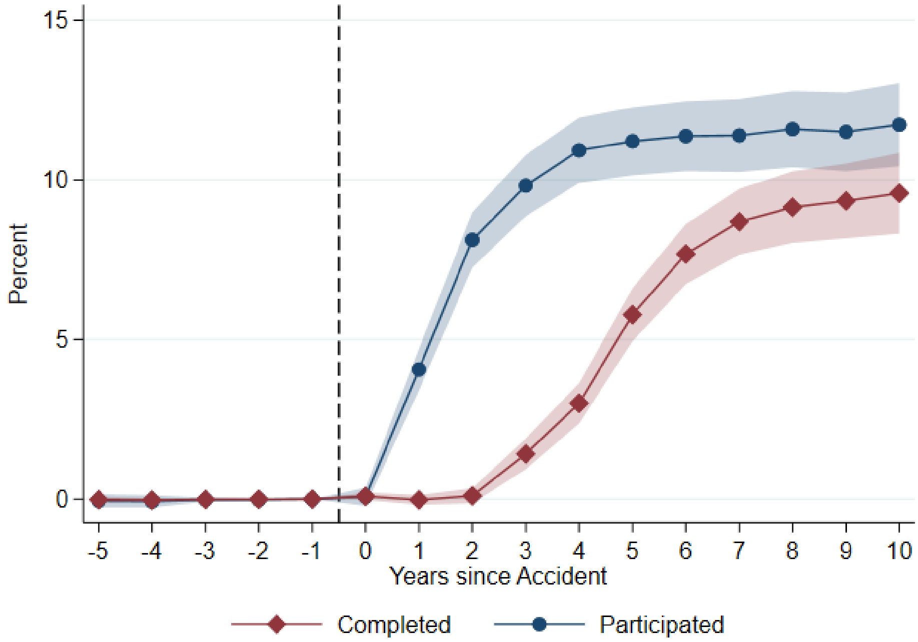


Non-Degree



Notes: This figure shows participation (measured in full-time equivalents) in degree and non-degree courses, split by the worker's initial educational attainment. *Basic* is primary and high school, and *Higher* is all post-secondary education. The graphs show the difference-in-differences in outcomes between the "Injury" and "Match" workers from Table 2, indexed to year -1. Shaded areas represent 95% confidence bands.

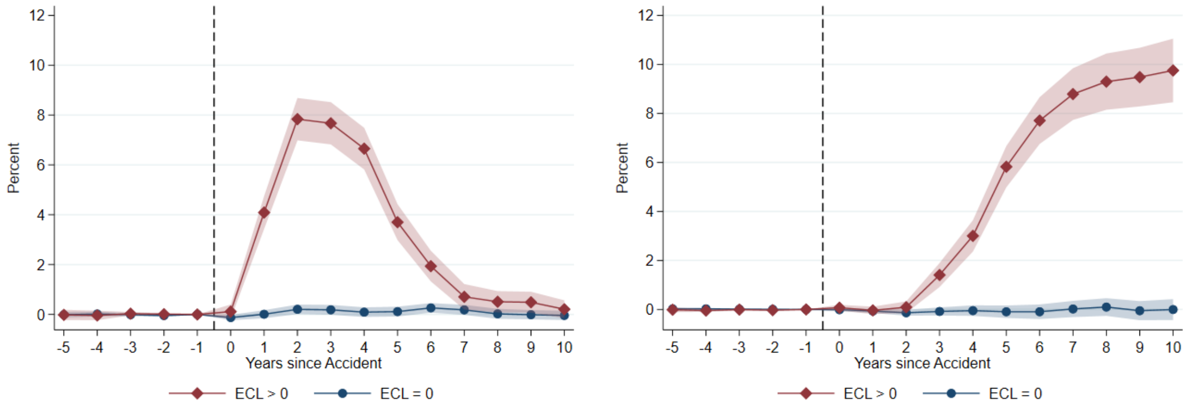
Figure A.8: Pursuit of Higher Degrees around Work Accident



Notes: This figure shows the participation and completion of higher degrees around work accidents. The figure focuses on workers who, before the work accident, had a secondary or vocational degree that gives access to higher education. The graphs show the difference-in-differences in outcomes between the "Injury" and "Match" workers from Table 2, indexed to year -1. Shaded areas represent 95% confidence bands.

Figure A.9: Pursuit of Higher Degrees by Earning Capacity Loss

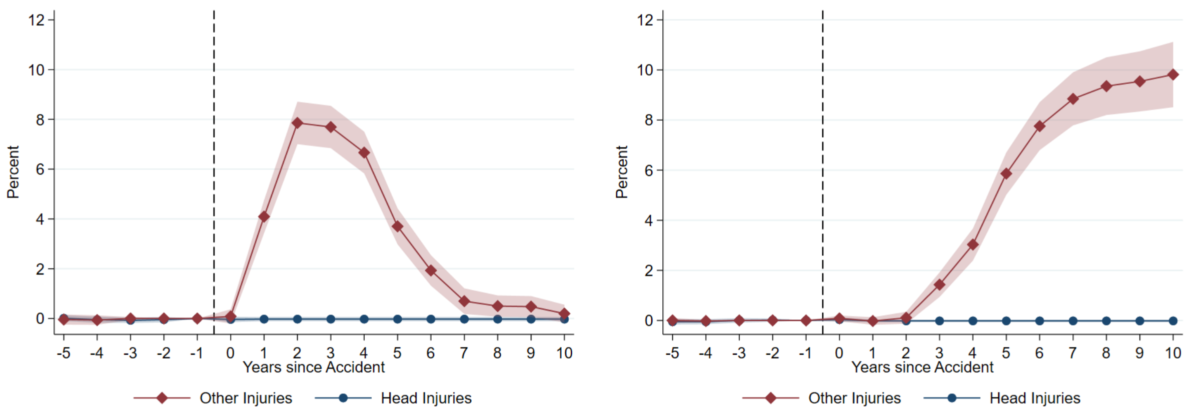
(a) Participation (b) Completion



Notes: The figure shows the participation in and completion of higher degrees around work accidents, split by whether the accidents generated an earning capacity loss (ECL). The figure focuses on workers who, before the work accident, had a secondary or vocational degree that gives access to higher education. The graphs show differences-in-differences in outcomes between the "Injury" and "Match" workers from Table 2, indexed to year -1. Shaded areas represent 95% confidence bands, estimated using the regression equation (1).

Figure A.10: Pursuit of Higher Degrees by Injured Body Part

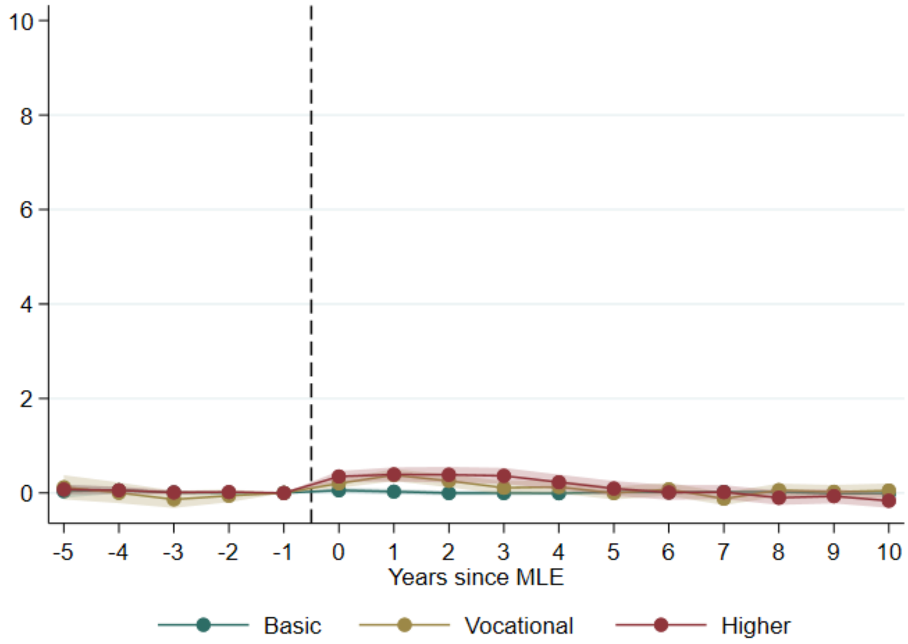
(a) Participation (b) Completion



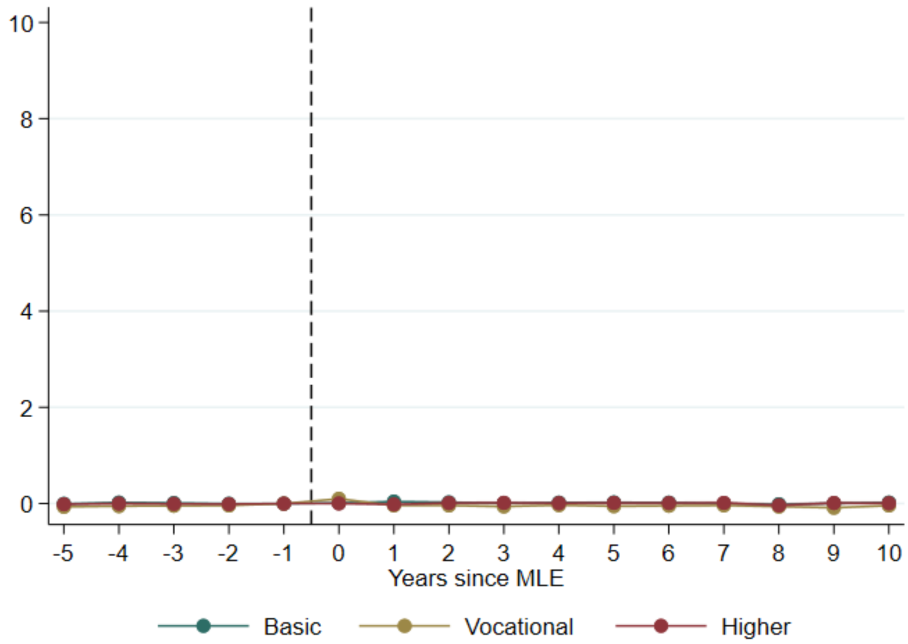
Notes: The figure shows the participation in and completion of higher degrees around work accidents, split by whether the injury caused Post Concussion Syndrome (PCS). Post Concussion Syndrome (PCS) is a typical brain damage diagnosis after accidents with symptoms that include persistent headaches, dizziness, and problems with concentration and memory, continuing after the normal recovery period of concussion. Head injuries constitute 6% of accidents and 0.4% of accidents cause PCS. See Figure A.9 for notes on the regression specification.

Figure A.11: Participation in Courses around Mass Layoff

(a) Degree



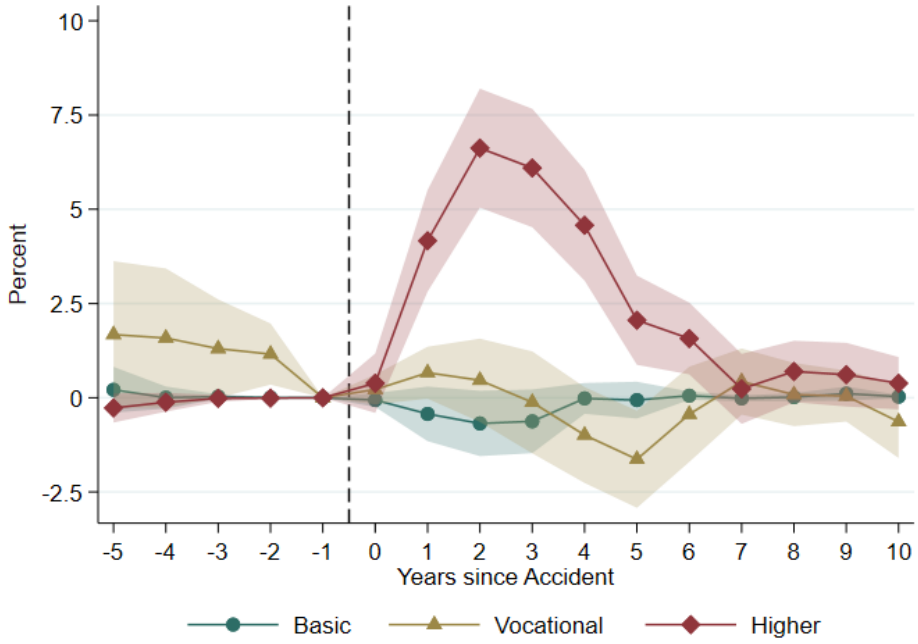
(b) Non-Degree



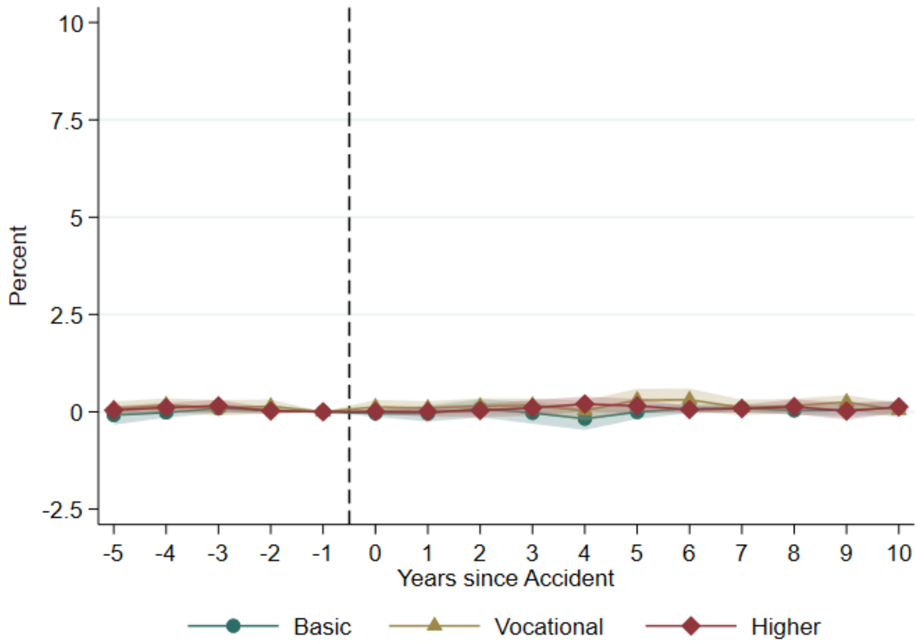
Notes: This figure shows participation (measured in full-time equivalents) in degree and non-degree courses by level of education. *Basic* is primary and high school (academic track), and *Higher* is all post-secondary education. This figure focuses on workers who, before the mass layoff, had a secondary or vocational degree that gives access to higher education. The graphs show differences-in-differences in outcomes between the “Displaced” and “Match” workers (using the matching strategy of Table 2), indexed to year -1. Shaded areas represent 95% confidence bands estimated using the regression equation (1).

Figure A.12: Participation in Courses around Accident

(a) Degree



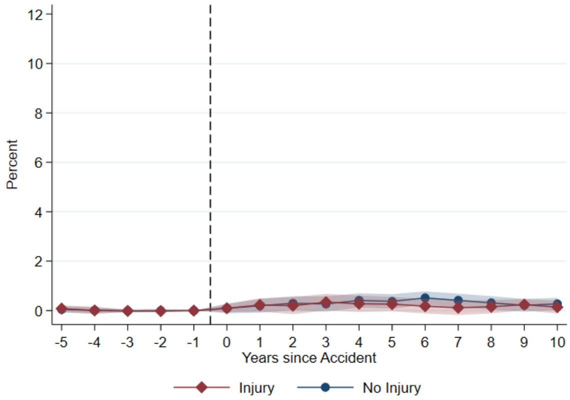
(b) Non-Degree



Notes: This figure shows participation (measured in full-time equivalents) in degree and non-degree courses by level of education. *Basic* is primary and high school (academic track), and *Higher* is all post-secondary education. This figure focuses on craft workers. The graphs show triple-differences in outcomes between the "Access" and "No Access, IPW" workers (defined in Table 3), each measured relative to their "No Injury" matches, and indexed to year -1. The "No Injury" workers correspond to the "Match" column in Table 2. Shaded areas represent 95% confidence bands.

Figure A.13: Outcomes around Temporary Work Injuries (Placebo Check): "Access" – "No Access"

(a) Enrollment in Higher Degrees

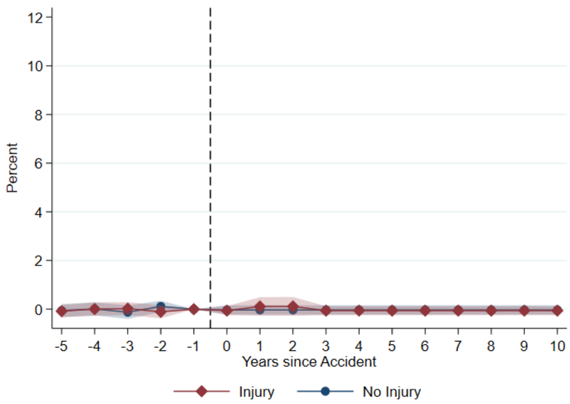


(b) Labor Earnings

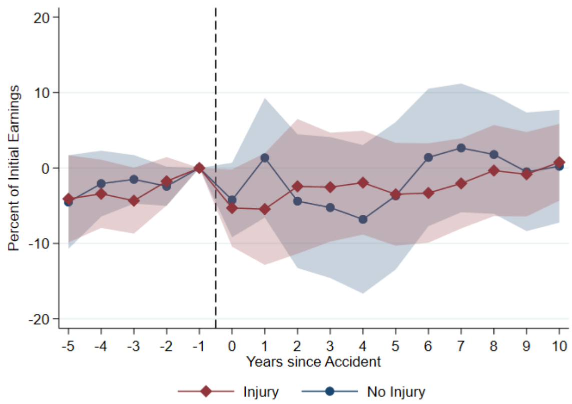
Notes: The figure studies temporary work injuries, defined as work accidents that AES assesses did not cause permanent loss of earning capacity or personal impairment to the worker. The plots show differences-in-differences between the "Access" and "No Access, IPW" workers, indexed to year -1. The figure focuses on craft workers. Panel (a) shows enrollment in higher degrees measured in full-time equivalents. Panel (b) shows labor earnings measured in percent of average earnings in year -1. Shaded areas represent 95% confidence bands, estimated using Equation (2).

Figure A.14: Outcomes around Work Accidents of Workers Age 55+ (Placebo Check): "Access" – "No Access"

(a) Enrollment in Higher Degrees



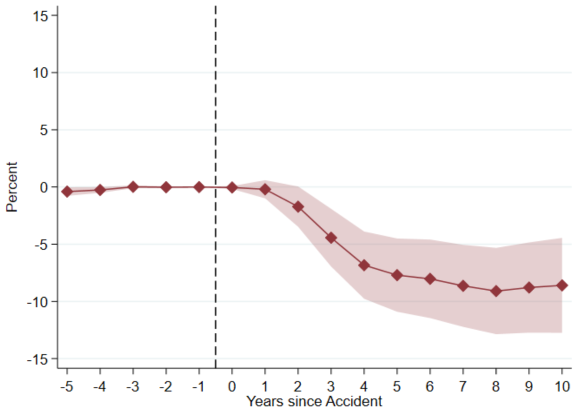
(b) Labor Earnings



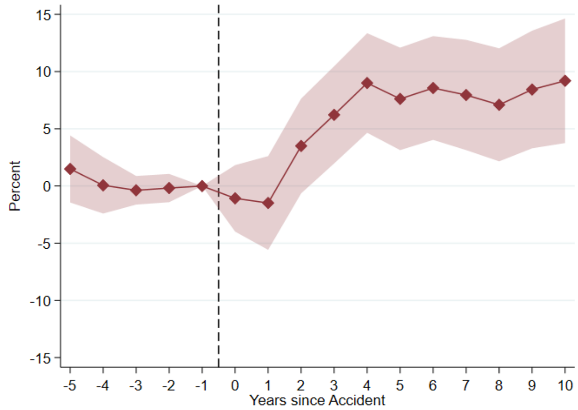
Notes: The figure restricts to workers above age 55. The plots show differences-in-differences between the "Access" and "No Access, IPW" workers from Table 3, indexed to year -1. The figure focuses on craft workers. Panel (a) shows enrollment in higher degrees measured in full-time equivalents. Panel (b) shows labor earnings measured in percent of average earnings in year -1. Shaded areas represent 95% confidence bands, estimated using Equation (2).

Figure A.15: Labor Supply around Work Accident (Triple Difference)

(a) Disability Insurance



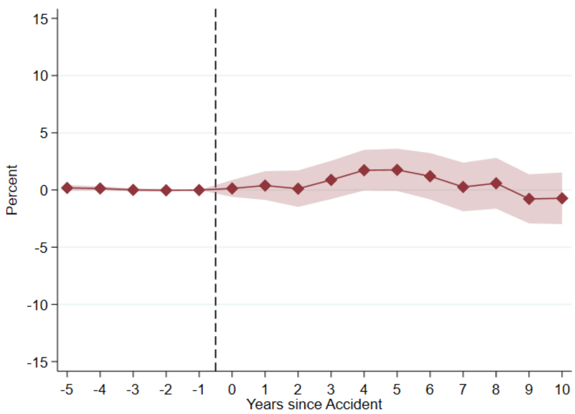
(b) Employed



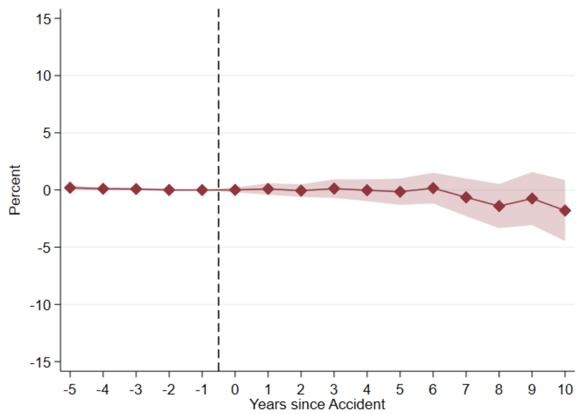
Notes: This figure shows the extensive-margin labor supply of workers. The figure focuses on craft workers. The graphs show triple-differences in outcomes between the "Access" and "No Access, IPW" workers (defined in Table 3), each measured relative to their "No Injury" matches, and indexed to year −1. The "No Injury" workers correspond to the "Match" column in Table 2. Shaded areas represent 95% confidence bands.

Figure A.16: Non-Means-Tested Pensions (Triple Difference)

(a) Early Retirement



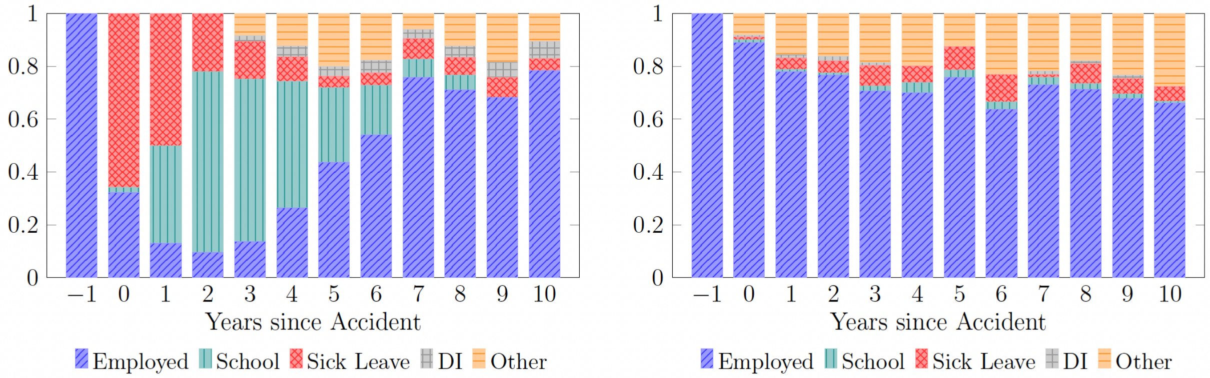
(b) Public Pension



Notes: This figure shows the receipt of pensions that are not means tested. The graphs show triple-differences in outcomes between the "Access" and "No Access, IPW" workers (defined in Table 3), each measured relative to their "No Injury" matches, and indexed to year −1. The "No Injury" workers correspond to the "Match" column in Table 2. Shaded areas represent 95% confidence bands.

Figure A.17: Potential Labor Supply of Compliers

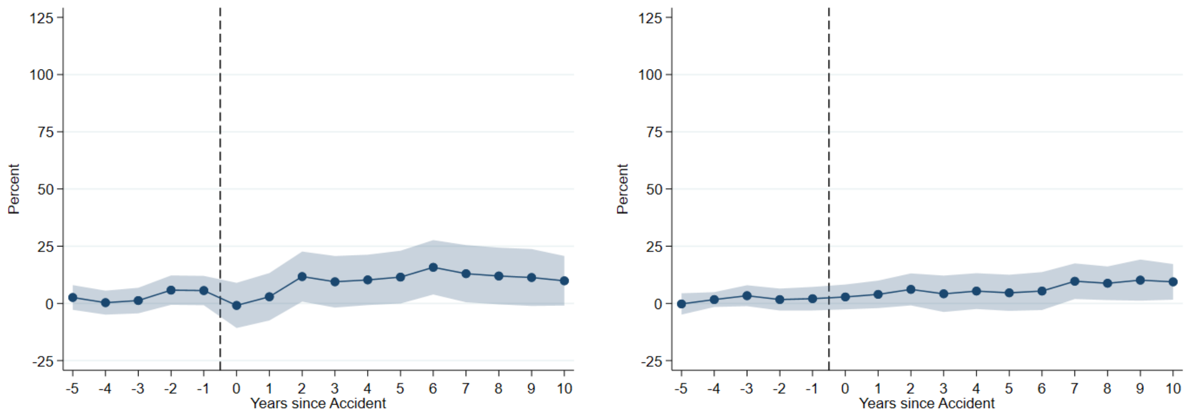
(a) Injury & Reskill (b) No Injury



Notes: This figure shows the labor supply of workers who comply with access to higher education by pursuing a higher degree after work accidents. *Employed* is fulltime employment. *School* is enrollment in a higher degree. *Sick Leave* refers to receiving sickness benefits. *DI* is disability insurance. *Other* is mainly unemployment and non-participation. Panel (a) reports treated complier means, estimated using Equation (4). Panel (b) reports the outcomes of their match workers (who do not experience a work injury in the event year).

Figure A.18: Antidepressant Prescription

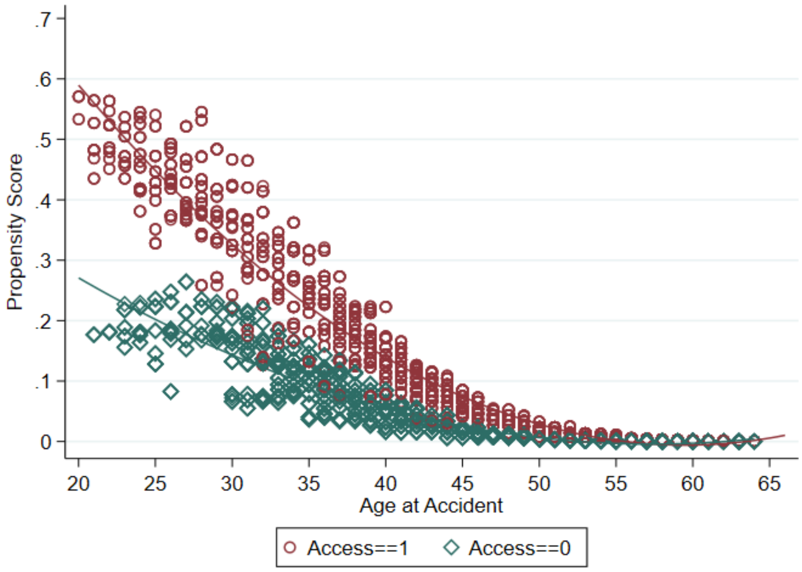
(a) Injury & Reskill (b) No Injury



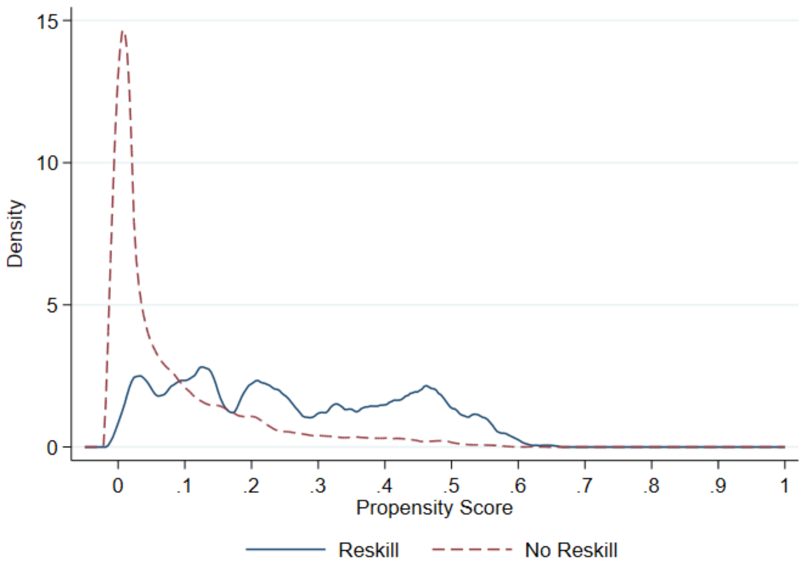
Notes: This figure shows the prescriptions of antidepressants of workers who comply with access to higher education by pursuing a higher degree after work accidents. Panel (a) reports treated complier means, estimated using Equation (4). Panel (b) reports the outcomes of their match workers (who do not experience a work injury in the event year).

Figure A.19: Propensity Scores

(a) By Age and Access Status



(b) Density by Treatment Status



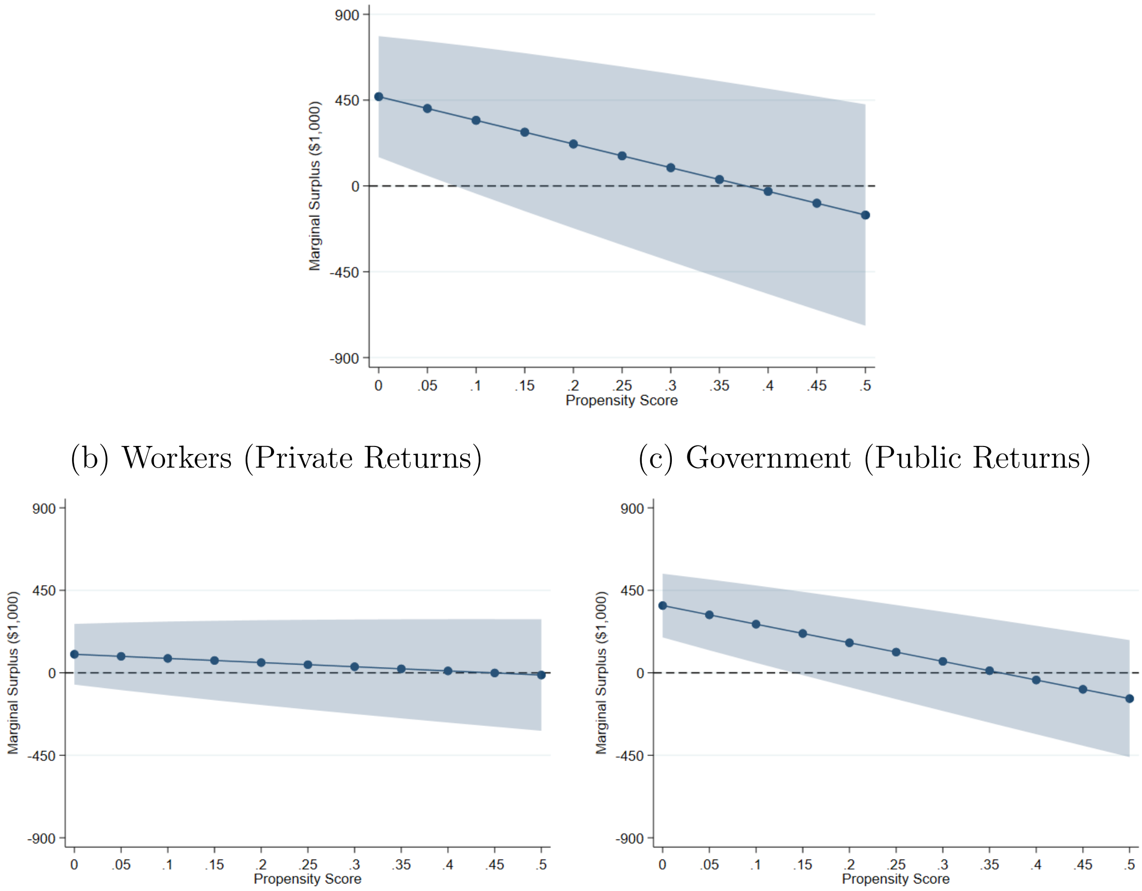
Notes: Panel (a) shows a binned scatter plot of estimated propensity scores for reskilling (Equations (12)-(14)) of workers of different ages and access to higher education. Each dot contains at least 5 observations, with variation around the lines of best fit reflecting differences in distances to education facilities. Panel (b) plots the distribution of propensity scores for treated ("Reskill") and non-treated ("No Reskill") workers, showing a continuous overlap between 0 and 0.5.

Figure A.20: Marginal Returns of Reskilling Workers of Age 40 ($1,000)

(a) Total (Social Returns)

(b) Workers (Private Returns)

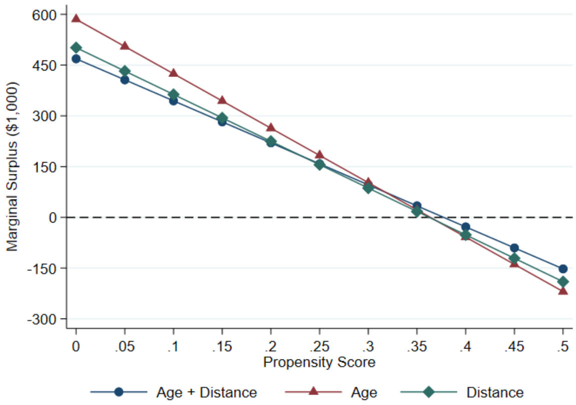
(c) Government (Public Returns)



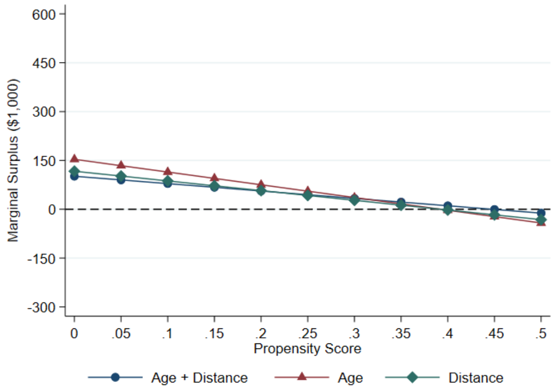
Notes: This figure shows the marginal returns on reskilling workers of age 40. Social returns (Panel (a)) is the sum of returns for workers (Panel (b)) and the government (Panel (c)), each defined as in Table 5. The shaded areas represent 90% confidence bands, estimated with a Bayesian bootstrap (Shao and Tu (2012)) of 1000 iterations over the propensity score and outcome equations (12)-(14) and (16) with weights drawn from a uniform distribution.

Figure A.21: Robustness of Marginal Returns Estimates

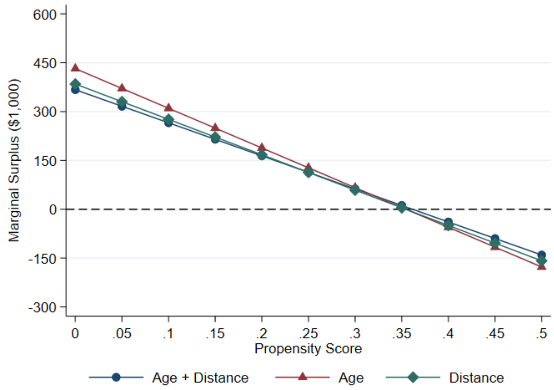
(a) Total (Social Returns)



(b) Workers (Private Returns)



(c) Government (Public Returns)



Notes: This figure shows the robustness of our marginal returns estimates to the choice of interacting covariate in the propensity score estimation. Social returns (Panel (a)) is the sum of returns for workers (Panel (b)) and the government (Panel (c)), each defined as in Table 5. The estimates represent the marginal returns of reskilling workers of age 40. The *Age + Distance* lines refer to our main specification described in Section 5.1.1. The Age lines only use worker age as the interacting covariate in the propensity score estimation, thus setting $\beta_4 = \beta_5 = 0$ in Equations (12)-(14). The *Distance* lines only use workers' distance to education facilities as the interacting covariate, thus setting $\beta_2 = \beta_3 = 0$ in Equations (12)-(14).

B Targeted Investment

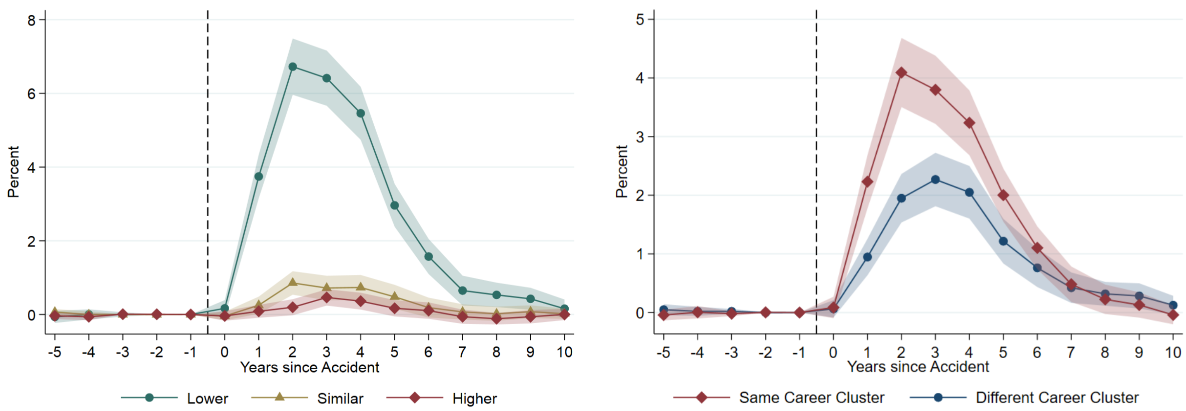
This section describes how we link degrees to their target occupations and sectors. These links form the basis of Figure B.1.

To guide the creation of the links, we exploit the correlations between workers' attained degrees and their occupations in the administrative data. For example, most workers with a bachelor's degree in "4087 Construction Architecture" are employed as "2142 Construction Architects."

For workers who have completed degree d, we rank occupations o by their shares in total employment of the workers. We also rank occupations by the share of their employees who have completed degree d. Based on these rankings, we manually verify the links from degrees to occupations. The list of degrees and target occupations is available at `www.andershumlum.com/s/target_occupations.xlsx`.

Figure B.1: Investment in Higher Degrees by Similarity of Target vs. Initial Occupation

(a) Physical Intensity (b) Career Cluster



Notes: This figure shows participation in higher degrees according to the similarity between the worker's initial job and the higher degree's target occupation. *Physical Intensity* is *"performing general physical activities"* (O*NET). "Similar" degrees target occupations with physical intensities within ± 1/2 standard deviations of the worker's initial job. *Career Clusters* are *"occupations in the same field of work that require similar skills"* (O*NET). The figure focuses on workers who, before the work accident, had a secondary or vocational degree that gives access to higher education. The graphs show differences-in-differences in outcomes between the "Injury" and "Match" workers from Table 2, indexed to year -1. Shaded areas represent 95% confidence bands, estimated using the regression equation (1).

C Inverse Probability Weighting

This section describes our inverse probability weighting (IPW) procedure for finding comparable workers who differ in their eligibility for higher education. The procedure follows Abadie (2005).

We first estimate propensity scores for having access to higher education:

$$p(\text{Access}_{ie-1} = 1) = \mu(X_{ie-1}), \tag{19}$$

where μ is a logistic link function, and X include first- and second-order terms of the variables listed in the "*Demographics*", "*Employment*", "*Education*", "*Occupation*", and "*Injury*" panel of Table 3. To be specific, X includes first- and second-order terms of age, hours worked, labor market income, hourly wages, job tenure, labor market experience, sickness benefits, physical- and cognitive ability requirements, occupational injury rates, earnings capacity loss, personal impairment, year of injury, and first-order terms of gender, cohabiting, having children of school age, owning property, working in the public sector (all of which are binary outcomes), and years of schooling. We then reweight our "No Access" workers to have the same average propensity score as our "Access" group. In particular, we assign each "No Access" worker i a weight of

$$w_i = \frac{\hat{p}(X_{ie-1})}{1 - \hat{p}(X_{ie-1})}. \tag{20}$$

We estimate the propensity scores separately by injury status and the education groups (craft, care, and other workers) defined in Table A.5. Table 3 validates that the IPW-weighted "No Access" workers are comparable to the "Access" group on the observables X.

C.1 Robustness Analysis

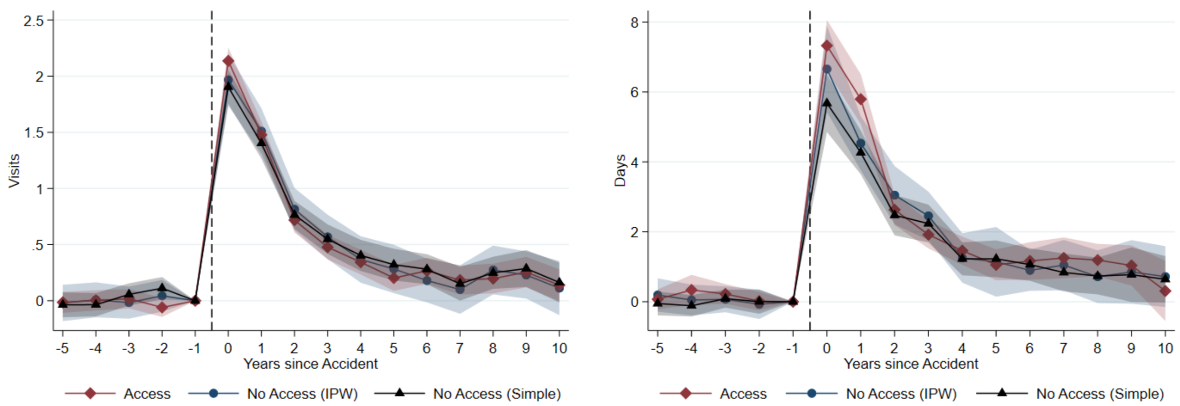
This section shows that our difference-in-difference estimates from Section 4 are robust to the inverse probability weighting (IPW) of the control group. To do so, we reproduce our first-stage and reduced-form estimates, only balancing on the immediate severity of the injuries and whether the workers are employed in the public sector.[83]

That is, we reweigh the "No Access" workers based only on the hospitalization (number and days of visits) in the year of the accident and an indicator for working in the public sector in the year before the accident (X in Equation (19)). We call this specification "No Access (Simple)". Figure C.1 confirms that the worker groups experience similar hospitalizations following their injuries.

Figure C.1: Hospitalization around Accident

(a) Number of Hospital Visits

(b) Days in Hospital



Notes: This figure shows the hospitalization of workers, split by whether the workers have access to higher education upon injury. The first two lines correspond to the "Access" and "No Access, IPW" columns of Table 3. The last lines reweigh the "No Access" workers only based on the hospitalization (number and days of visits) in the year of the accident and an indicator for working in the public sector in the year before accident. The graphs show differences-in-differences in outcomes between the "Injury" and "Match" workers from Table 2, indexed to year -1. Shaded areas are 95% confidence bands.

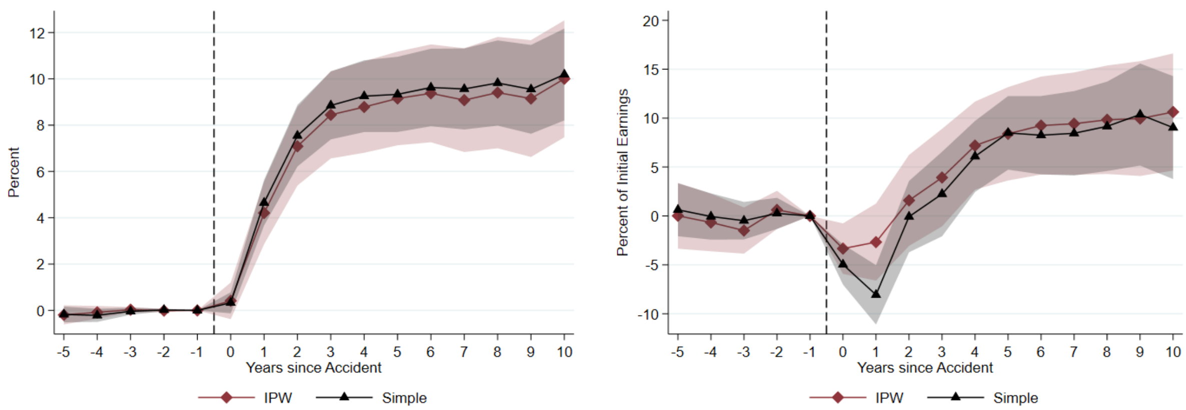
Figure C.2 shows our main triple-difference estimates using either "No Access (IPW)" or "No Access (Simple)" as the control group. The figure shows that the first-stage and reduced-form results are robust to the IPW method. These results highlight our main conclusions for the effects of reskilling do not hinge on the specific reweighing of the "No

[83]The "No Access (Raw)" group experiences milder injuries than the "Access" workers, spending on average 4.5 additional days in the hospital in the year of the accident (instead of 7.5 additional days). So, to ensure we compare similar injuries, "No Access (Simple)" reweigh the control group based on the hospitalization in the year of the accident. In addition, our "Access" group of craft workers is more likely to be employed in the private sector. Hence, because public sector employees face better job security immediately following work accidents, we also reweigh the control group based on whether workers were employed in the public sector.

Access" control group.

Figure C.2: Outcomes around Work Accident (Triple Differences)

(a) Participated in Higher Degree (b) Labor Earnings



Notes: This figure shows outcomes of workers around work accidents according to workers' initial access to higher education. The plots are triple differences, where the first difference is between the "Access" and "No Access" workers ("IPW" and "Simple", respectively), the second difference is between the "Injury" and "No Injury" workers, and the third difference is indexed to year -1. Shaded areas represent 95% confidence bands.

D Care Workers

The main analysis in Section 4 focuses on craft workers who all have access to higher degrees that target occupations with lower physical intensity than their previous jobs. In this section, we study care workers whose higher degrees have similar physical intensity. An example is nursing assistants who may enroll in the bachelor's program in nursing.

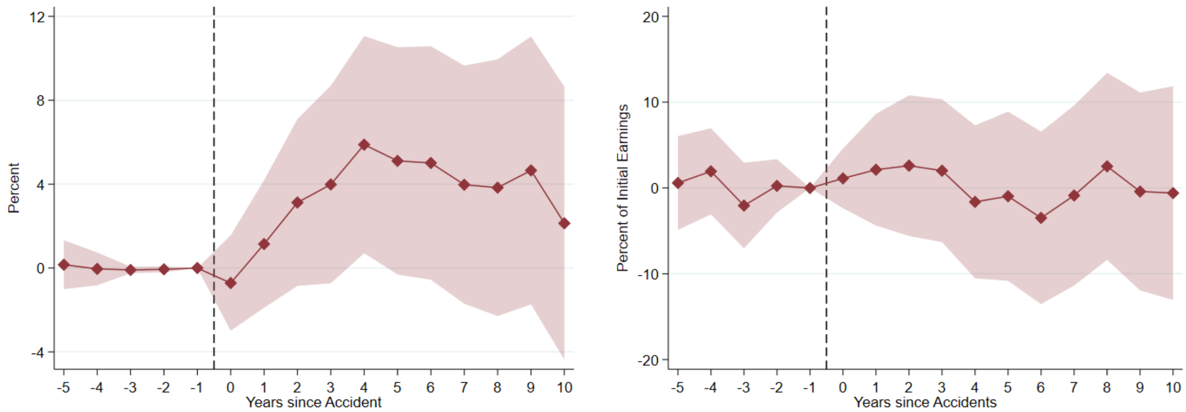
Figure D.1.(a) shows the care workers' pursuit of higher degrees around work accidents. Comparing the responses to our main Figure 5 delivers two insights. First, care workers invest less in human capital after work accidents. Ten years after the accident, only around 3% of care workers have enrolled in a higher degree due to the injury, which is markedly less than the 10% effect in our main sample (Figure 5.(b)). Second, because care workers constitute a smaller share of work injuries, we have less precision in estimating the effects in Figure D.1. Combined, these two effects (lower point estimates and less precision) imply that we cannot detect a statistically significant first-stage relationship between access to higher education and subsequent pursuit of higher degrees.

Figure D.1.(b) shows that workers who have access to higher degrees with similar or higher physical demands do not fare better in the labor market after experiencing a work injury.

Taken together, the null effects in Figure D.1 suggest that access to higher degrees only helps workers if the programs target jobs that are less physically demanding.[84]

Figure D.1: Outcomes around Work Accidents: Care Workers (Triple Differences)

(a) Participated in Higher Degrees (Stock) (b) Labor Earnings



Notes: This figure shows outcomes of workers around work accidents according to workers' initial access to higher education. The figure focuses on care workers. The plots are triple differences, where the first difference is between the "Access" and "No Access" workers ("IPW" and "Simple", respectively), the second difference is between the "Injury" and "No Injury" workers, and the third difference is indexed to year -1. Panel (a) shows enrollment in higher degrees measured in full-time equivalents. Panel (b) shows labor earnings measured in percent of average earnings in year -1. Shaded areas represent 95% confidence bands, estimated using the Equation (2).

[84]Because care workers are predominantly female, the smaller impact of the access policy could also reflect gender differences in reskilling behaviors. However, two pieces of evidence counter this hypothesis. First, zooming in on the *male* care workers, we find similar insignificant effects of the access policy on their human capital investment and labor earnings. Second, studying the craft workers, Table A.9 shows that *women* are more likely to reskill after injuries.

E Cost-Benefit Evaluation

This section describes our approach to estimating the costs and benefits of higher education for injured workers. We evaluate the incidence for a worker who suffers an injury at age 32 (the average among our compliers, cf. Table A.9) and retires at age 65.[85] We base our calculations on the reduced-form estimates in Equation (2), assuming the estimates are stable after year 10. All nominal values are deflated to their 2015 US dollar value.

The benefits include post-tax earnings for workers and labor income taxes for the government, which we calculate by applying the median tax rate in the year prior to injury (32.2%) to the labor income effects estimated in Figure 6.

For public transfers, we first estimate the effect of higher education on receiving different transfers, including disability benefits (shown in Figure A.15) and unemployment benefits. Section 2 describes the transfers. We then scale these effects with the transfer rates collected from the government budget.[86]

Education expenses include tuition and school-related transfers. Tuition costs amounts to approximately $16,500 a year per full-time student. We collect the tuition costs from the government budget.[87] The transfers include the State Education Support (SU) and reskilling benefits.

We then calculate the present-discounted value of each stream of costs and benefits, assuming a real discount rate of 6% per year. The internal rate of return (IRR) is the discount rate that makes the total net present value equal to zero.

E.1 Mental Health

This section describes how we include the effects on mental health in the cost-benefit calculations.[88] We include expenditures related to mental health in the form of co-

[85] Figure A.16 supports the assumption that human capital investment does not affect the age of public pension retirement of injured workers.

[86] The transfer rates, linked to the transfer codes of the DREAM register, are available at `www.andershumlum.com/s/dream_transfer_rates.xlsx`.

[87] The "rate catalogs" (Takstkataloger, in Danish) list the cost per full-time student by detailed degrees.

[88] Again, we evaluate the incidence for a worker at age 32 (the average among our compliers, cf. Table A.9) up until age 65, assuming that the effects of higher education on mental health are zero after

pay and reimbursements related to treatment (medication, counseling) and the effect on quality-adjusted life years (QALYs).

First, we calculate the average yearly costs of medication for three categories of prescription drugs related to mental health: antidepressants (ATC-codes N06A), sleep medication (ATC-codes N05C), and painkillers, including opioids (ATC-codes N02). We use the average price per Defined Daily Dose (DDD)[89] within each category and multiply by 365 days to get the yearly cost of each type of medication. We split this cost into co-pay for workers and subsidies from the government using the reimbursement thresholds provided by the Danish Medicines Agency.[90]

In addition to medication costs, we include the costs of counseling offered by registered psychologists and psychiatrists using standard rates of co-pay and reimbursement agreed to by the state and unions.[91]

The monetary value of mental health in terms of life quality is the most difficult component to assess. Therefore, we take a conservative approach and apply the lower bounds of existing estimates. In particular, the literature has estimated depression to lower QALYs by 20% to 40% (Fryback et al. (1993); Lave et al. (1998); Jia et al. (2015); Williams et al. (2023)) and the monetary value of a QALY to range between \$20,000 and \$75,000 (Huang et al. (2018); Chilton et al. (2020); Himmler (2021)).[92] Combining the two lower bounds implies a burden of depression of at least \$4,000 per year. We multiply this burden with the effect of reskilling on antidepressant use (the outcome in Figure 8) to quantify the impact on life quality.

Table E.1 shows the benefits (avoided costs) of reskilling on mental health. Reskilling generates a social surplus from mental health of \$51,000 per reskilled worker. Workers

retirement. Our estimates serve as lower bounds of the true effect if reskilling continues to have positive mental health benefits after retirement.

[89]The DDD is defined by WHO and adapted by the Danish Medicines Agency to provide prices per DDD for each drug. A full list of prescription drug prices is available at `www.medicinpriser.dk`.

[90]The reimbursement thresholds are available at `https://laegemiddelstyrelsen.dk/en/reimbursement/calculate-reimbursement/reimbursement-thresholds/`.

[91]The rates are available at `https://www.dp.dk/raadgivning/selvstaendig/psykolog-med-ydernummer/honorarer-afregning-og-omsaetning/praksishonorarer/`.

[92]Institute for Clinical and Economic Review (2020) uses a range between \$50,000 and \$200,000.

reap 57% of the surplus, driven mainly by the effect on QALYs, while the government avoids covering costly treatments.

Table E.1: Benefits (Avoided Costs) of Higher Education on Mental Health

	Per retrained worker ($)	Percent of total
Workers	**29,157**	**57.2**
Treatment co-pay (medication, counseling)	7,245	14.2
Quality-adjusted living years (QALYs)	21,913	43.0
Government	**21,840**	**42.8**
Treatment subsidies (medication, counseling)	21,840	42.8
Total	**50,997**	**100.0**

F General Equilibrium Effects

Reskilling programs could affect the labor market equilibrium. For example, a large expansion of reskilled workers could bid down wages (Heckman, Lochner, and Taber (1998)). In this section, we assess how sensitive the optimal rates of reskilling are to incorporating such equilibrium effects. To do so, we embed our estimated treatment effects into a calibrated model of the labor market.

F.1 Model

The labor earnings of a worker i are the product of the market wage and his human capital:

$$E_i = w \times H_i. \tag{21}$$

Wages equalize the demand and supply of human capital:

$$H^D = w^{-\epsilon} \tag{22}$$

$$H^S = H^N + H^I(p), \tag{23}$$

where ϵ is the wage elasticity of labor demand, and aggregate labor supply is the sum of human capital supplied by non-injured (N) and injured (I) workers. The human capital of injured workers depends on the reskilling rate p. We assume that labor supply is inelastic to wages to focus on the role of labor demand in absorbing the reskilled workers.

Section 5.1 estimates the impact of reskilling p on individual earnings, keeping market wages fixed at their current levels w_0. As Panel (a) of Figure F.1 shows, these earnings effects correspond to the labor market surplus when labor demand is perfectly elastic. However, when labor demand is finitely elastic, as in Panel (b), the reskilled workers face decreasing marginal returns, dampening the surplus from reskilling.

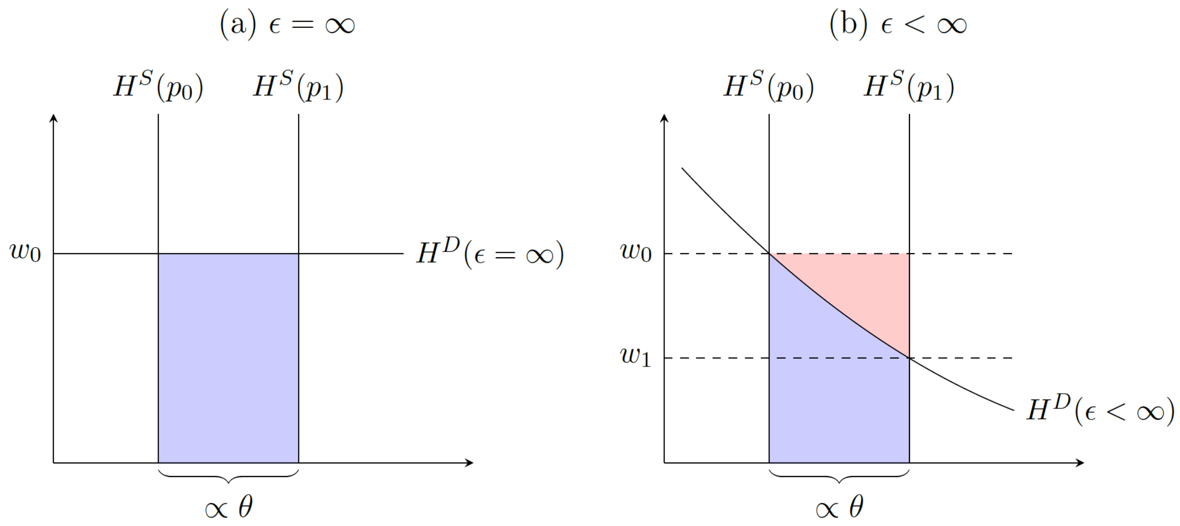
The share of lost surplus in general equilibrium (the red triangle in Panel (b) as a fraction of the blue rectangle in Panel (a)) grows in the size of the labor supply shock.

The size of the shock, in turn, depends on the share of injured workers in labor supply:

$$\theta = \frac{H^I(p_0)}{H^N + H^I(p_0)}. \tag{24}$$

Consequently, when injured workers constitute a small fraction of the aggregate labor supply, the labor market surplus from reskilling remains closer to the estimates from Section 5.1.

Figure F.1: Labor Market Surplus from Reskilling by Elasticities of Labor Demand ϵ



Notes: This figure illustrates how the labor market surplus from increasing the reskilling rate (from p_0 to p_1) depends positively on the elasticity of labor demand ϵ (flatness of the labor demand curve) and negatively on the fraction of injured workers in labor supply θ (scaling the horizontal shift in the labor supply curve).

In Appendix F.3.1, we formalize the graphical intuitions from Figure F.1 by solving for the labor market equilibrium as a function of the reskilling rate p. In particular, we show that the labor market surplus from increasing reskilling is (i) increasing in the elasticity of demand ϵ, and (ii) decreasing in the share of injured workers in aggregate labor supply θ.

F.2 Calibration

Elasticity of labor demand ϵ

Hamermesh (1996) and Lichter, Peichl, and Siegloch (2015) survey existing estimates of labor demand elasticities to lie between 0.15 and 0.75 with a focal estimate of 0.5.

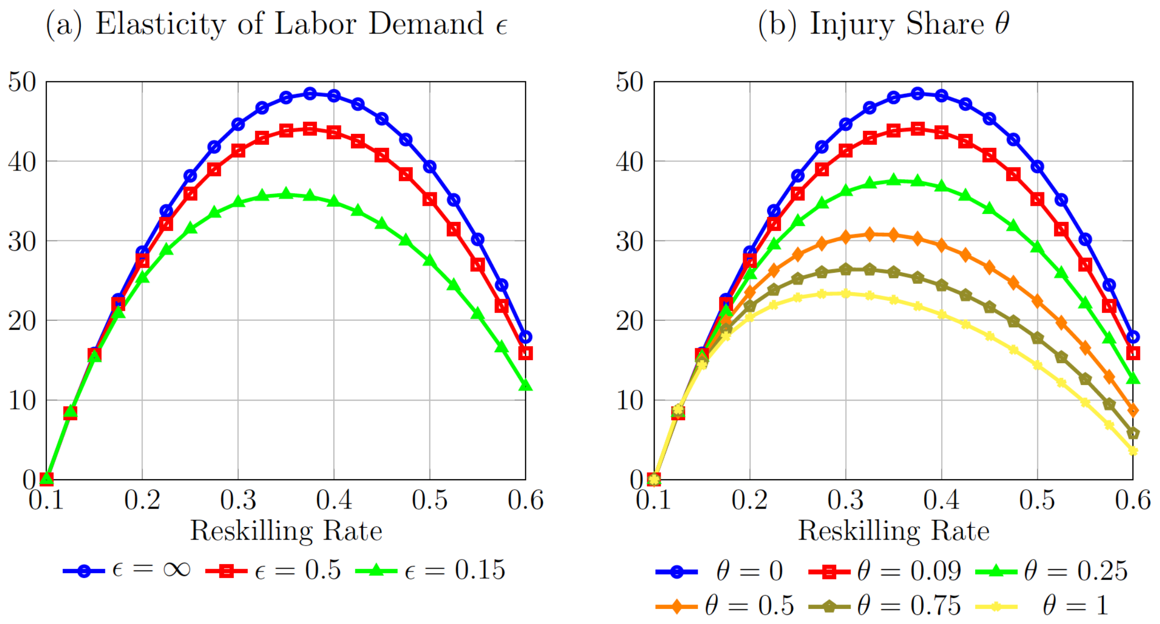
Injury share θ

Appendix F.3.2 calibrates the share of injured workers in aggregate labor supply. We first estimate the labor supply of injured workers $H^I(p)$ by scaling the treatment effects on earnings $f^E(p)$ with the number of injured workers per year. Next, we estimate the aggregate labor supply $H^S(p_0)$ as the total annual labor earnings in the occupations of reskilled workers. Combining the estimates, we obtain a share of $\hat{\theta} = \frac{\hat{H}^I(p_0)}{\hat{H}^S(p_0)} = 0.09$.

F.2.1 Simulations

Figure F.2 simulates the social surplus of increasing the reskilling rate from its current level. We simulate the surplus under various values of the elasticity of labor demand (Panel (a)) and the share of injured workers in aggregate human capital (Panel (b)). The cases of perfectly elastic labor demand ($\epsilon = \infty$) or infinitesimal injury share ($\theta = 0$) correspond to the counterfactuals from Section 5.3.

Figure F.2: Social Surplus of Increasing Reskilling at Different Parameter Values



Notes: This figure shows the social surplus of increasing reskilling from its current rate of 15% under various values of (*a*) the elasticity of labor demand ϵ (fixing the current injury share θ at 0.09) and (*b*) the current share of injured workers in aggregate human capital θ (fixing the elasticity of demand ϵ at 0.5).

Figure F.2 shows that the optimal reskilling rates are fairly robust to labor market equilibrium effects. For example, by lowering the labor demand elasticity to 0.5 (the focal estimate in the literature) and setting the injury share to 0.09 (the actual share), the optimal rate of reskilling decreases from 38% to 37%, and the maximum social surplus falls by 9%. Lowering the elasticity of labor demand even further to 0.15 (the lower bound in the literature), the optimal rate of reskilling drops to 35%, and the potential surplus decreases by 26%. The robustness of the optimal reskilling rates to labor market equilibrium effects partly reflects that injured workers constitute a minor fraction of aggregate labor supply $\theta = 9\%$. That said, by raising the injury share to 50%, the optimal rate of reskilling only falls to 33%.

F.3 Technical Details

F.3.1 Labor Market Equilibrium

The labor market clears the demand and supply of human capital:

$$H^D = w^{-\epsilon} \tag{25}$$

$$H^S(p) = H^N + H^I(p). \tag{26}$$

We normalize the current level of aggregate human capital $H^S(p_0)$ to 1 and define $h(p) = \frac{f^E(p)}{f^E(p_0)} - 1$. The aggregate human capital is then

$$H^S(p) = 1 + \theta h(p), \tag{27}$$

where $\theta = \frac{H^I(p_0)}{H^N + H^I(p_0)}$ is the current share of injured workers in aggregate human capital.

The labor market surplus is the area under the labor demand curve. The surplus per injured worker is

$$\begin{aligned} S(p) &= \frac{f(p_0)}{\theta} \int_{1-\theta}^{1+\theta h(p)} H^{-1/\epsilon} dH && (28) \\ &= \frac{f(p_0)}{\theta} \left(\frac{\epsilon}{\epsilon - 1} \right) \left[(1 + \theta h(p))^{\frac{\epsilon-1}{\epsilon}} - (1-\theta)^{\frac{\epsilon-1}{\epsilon}} \right], && (29) \end{aligned}$$

which reduces to the partial-equilibrium expression $f(p)$ when labor demand is infinitely elastic ($\epsilon \to \infty$), or injured workers constitute a vanishing of aggregate labor supply ($\theta \to 0$).

The general-equilibrium surplus from increasing the reskilling rate to $p > p_0$,

$$S(p) - S(p_0) = \frac{f(p_0)}{\theta}\left(\frac{\epsilon}{\epsilon - 1}\right)\left[(1 + \theta h(p))^{\frac{\epsilon-1}{\epsilon}} - (1 + \theta h(p_0))^{\frac{\epsilon-1}{\epsilon}}\right], \tag{30}$$

is increasing in ϵ and decreasing in θ.

F.3.2 Calibration

Injury share θ

The share of injured workers in aggregate human capital is

$$\theta = \frac{H^I(p_0)}{H^S(p_0)} = \frac{I \times f^E(p_0)}{E_0}, \tag{31}$$

where I is the number of injured workers, f^E is the treatment effects of reskilling on earnings from Equation (9), and E_0 is the total annual earnings in the occupation.[93] For I, we use the number of workers per year who lose earning capacity from a physical work accident (the population of workers for the causal estimates in Section 5.1), corresponding to row 4 of Table A.2. For E_0, we assume that labor markets are segregated by four-digit occupations and use Equation (4) to estimate the total annual labor earnings in the four-digit occupations of reskilled workers. For $f^E(p)$, we convert the annual estimates from Tables A.14 and A.16 into lifetime values of workers aged 40 using Equation (18).[94,95] Combining the estimates, we obtain a share of $\hat{\theta} = 0.09$.

[93] We set $H^I(0) = 0$ following the result in Table 4 that injured workers only transition into cognitive occupations if they are reskilled.

[94] By using lifetime earnings for injured workers f but annual earnings for aggregate labor supply H_0^S, we take into account that reskilling affects the stock of human capital.

[95] The effect of reskilling p depends on its distribution across worker ages. We use, for simplicity, the estimates for workers of age 40.